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Three Essays on the Housing Market and Financial Intermediaries

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THREE ESSAYS ON THE HOUSING MARKET AND FINANCIAL INTERMEDIARIES

by

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ABSTRACT

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My dissertation utilizes the valuable information present in forward looking financial intermediaries and effects of the housing market on macroeconomy. In the second chapter, I study the dynamic relationship in the shadow banking system. Particularly, I investigate the short-run and the long-run relationship among the financial assets of the money market funds, the commercial paper, and the repurchase agreement markets by undertaking a co-integration analysis of quarterly data over the 1985-2013 period. The evidence suggests that there exists a common long-term cointegrating trend among these three components of the shadow banking system. Any disequilibrium in this long-run relationship among these variables is corrected by movement in the financial assets of the money market funds. The Beveridge-Nelson decomposition from the estimated cointegrating relationship shows that the cyclical component in the money market funds is large and captures the huge swings in these markets during the financial crisis. My results are also robust to the exclusion of the financial crisis, and it reveals the changing role of the commercial paper and the repurchase agreement market in the shadow banking system.

The third chapter of my dissertation examines the impact of housing price shocks on tradable and non-tradable employment in the U.S. states over 2001-2014 period. For this purpose, I use a multivariate structural VAR model with agnostic identification as proposed

by Uhlig (2005). This method imposes sign restrictions on some variables in the VAR system but does not restrict the response of employment. I find significant response of employment to house price shocks, with non-tradable employment being more responsive than tradable employment on average. My findings also suggest that the employment response to house price shock is very persistent across states. There is also significant heterogeneity in the persistence as well as the magnitude of response across different states with states with most volatile housing market responding more to the house price shocks.

In the fourth chapter, I apply the present value model to explain the movements in house price-income ratio in OECD countries over the period 1975-2015. Using state-space model, we decompose the movements in price-income ratio into expected housing return and expected income growth since price-income ratio is a forward looking variable. The evidence suggests that both expected income growth and expected housing price growth are significant in explaining movements in the price-income ratio, while there is a heterogeneity among all countries. I find a positive correlation between expected income growth and expected housing returns. The variance decomposition of the present value of price-income ratios shows that the most variation in the present-value component is explained in the housing return.

To

my parents,

my brothers,

and my sister.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Chapter 1

Introduction

One of the unique features of the financial crisis of 2007-2008 was the central role played by the financial intermediaries in both causing and exacerbating the great recession. In the financial markets, the shadow banking system is positioned similar to the traditional banking, but with some significant differences. Over time, the size of the shadow banking system has become comparable to the traditional banks in the U.S financial system. When subprime mortgages faced a big negative shock due to a sharp plunge in the housing market before the financial crisis, there were significant defaults in the short-term debt market which were linked to the subprime mortgages. The significant increase in the financial market risks also coincided with a run in the shadow banking system. Also, there is a consensus about the role of the housing market in causing and exacerbating the recent financial crisis. The financial crisis of 2008-2009 renewed the interest of policymakers and researchers in the dynamic relationship between the housing market and macroeconomy. My dissertation looks at financial intermediaries as well as the impact of housing markets on macroeconomics.

In the second chapter, I examine the long-run and the short-run relationship among these markets by using a time-series econometric approach. My results show that the money market funds, the commercial paper and the repo markets move together in the long-run. Further, any deviation in the shared long-run equilibrium forces the money market funds to error-correct to restore the equilibrium relationship on this long-run path.

This provides some rationale for the simultaneous growth of the commercial papers and the repo market with the growing balance sheet of the money market funds. Further, my results from the trend-cycle decomposition show that the cycle of the money market funds is relatively greater than the cyclical component of the other two variables. This supports the results from the error correction model.

The third chapter of my dissertation examines the effect of housing prices on employment by using time-series data on 45 U.S. states over the sample period 2001-2015. I also examine whether there is a differential impact of housing prices on non-tradable employment as compared to the tradable employment. To do so, I use a multivariate structural VAR model with sign restrictions. I assume that a positive shock to housing prices does not lead to a decline in income and building permits and an increase in non-performing loans for 12 months while I keep the response of employment to the housing price shock unrestricted. My results show significant response of employment to the housing price shock with a hump-shaped response for most of the states. There is significant heterogeneity, however, in the magnitude of responses. On average I find that states with higher volatility in housing prices have higher response of non-tradable employment to the housing price shock. I also find that states with higher correlation between consumption cycle and housing price cycles are also the states with relatively higher response of non-tradable employment as compared to the tradable employment.

In the fourth chapter, I use the present value model to explain the movements in house price-income ratio in OECD countries over the period 1975-2015. By using the state space model, I explained that the price-income ratio may move due to a change in expected income and price growth, which are stationary, and the residual component, which is non-stationary. I find that both expected income growth and expected price growth are significant in explaining movements in the price-income ratio. In addition, I find that the residual component that may explain the regulation and structural feature of the housing market is also significant, while for all countries, there is a significant heterogeneity. My findings suggest that the correlation between expected income and the residual component is positive for all countries.

Chapter 2

The Dynamic Relationship Among the Money Market Mutual Funds, the Commercial Paper Market and the Repo Market

2.1 Introduction

One of the unique features of the financial crisis of 2007-2008 was the central role played by the financial intermediaries in both causing and exacerbating the great recession. Financial intermediaries are shadow banks which use short-term funds in money markets to purchase assets with long-term maturities.[1] In the financial markets, the shadow banking system is positioned similar to the traditional banking, but with some significant differences. Traditional banks are insured by the FDIC. They also had an exclusive access to the Federal Reserve's discount window during the crisis. However, the shadow banking system is largely unregulated and not backed by a federal agency at least before the financial crisis.[2] Over time, the size of the shadow banking system has become comparable

[1] Assets with long-term maturities are credit card loans, residential mortgages and auto loans (Krishnamurthy et al. (2014)).

[2] Given the extraordinary impact of the recent crisis, the U.S. Treasury department created a temporary guarantee program (TGP) for Money Market Funds.

to the traditional banks in the U.S financial system.[3]

In the shadow banking system, the money market funds (MMFs hereafter), the commercial paper (CP hereafter) market and the repurchase agreement (repo hereafter) market are the three main players. Figure 1.1 shows the relationship between the MMFs, the CP and the repo markets as the three main funding sources for the shadow banking system in the U.S. The MMFs are one of the biggest cash players in the shadow banking system; the largest portion of this cash is allocated to collateralized repo and the CP market (Krishnamurthy et al., 2014). Prior to 1970, MMFs invested mainly in the U.S Treasury debt. However, since 1970, they became an alternative to traditional banks, and a new source of deposits for investors as they offered slightly higher returns than the conventional bank deposits. The significant increase in financial assets of MMFs also coincided with the development of the CP and the repo markets. At the same time, the simultaneous development of the CP and the repo markets facilitated the growth of the MMFs, as they became an important source of investments for the MMFs. These two markets provided a market for private sector debt that was considered relatively safe, flexible and paid interest (Anderson et al., 2009).

When subprime mortgages faced a big negative shock due to a sharp plunge in the housing market before the financial crisis, there were significant defaults in the short-term debt market which were linked to the subprime mortgages. The significant increase in the financial market risks also coincided with a run in the shadow banking system. As a result, the financial assets of the MMFs decreased by a trillion dollars between 2008 to 2010. At the same time, the financial assets of the CP and the repo markets in the same period declined by \$0.7 trillion and \$17 million respectively. The academic literature also started paying attention to these financial intermediaries since the financial crisis. See for example, Gorton and Metrick (2012), Gorton et al. (2010), and Krishnamurthy et al. (2014) among others. However, most of these papers have provided a narrative explanation for the causes of the crisis and the role of different markets in propagating the crisis.

[3]Gorton et al. (2010) show that before the 2007-2008 financial crisis the assets of the shadow banking system were as large as the asset of traditional banks.

We contribute to the existing nascent literature on the MMFs, the CP, and the repo markets by examining the dynamic relationship between these three markets over time. In particular, we are interested in testing the anecdotal evidence about the simultaneous development of the MMFs, the CP, and the repo markets. To do so, we examine the existence of a long-run relationship in the financial assets of these three markets by modeling the long-run cointegrating relationship between these three variables. To examine which of these variables adjust to correct for the disequilibrium in the short-run, we use a vector error correction methodology. Using the information from the long-run cointegration model, we also decompose the movements in the financial assets of the MMFs, the CP, and the repo markets into a trend and a cycle. This allows us to measure the extent of movement in these variables that are permanent and transitory.

Our results show that the financial assets of the MMFs, the CP, and the repo markets share a long-run equilibrium relationship, i.e., they are cointegrated. Any deviation from this long-run equilibrium is corrected by the subsequent movements in at least one of these three markets. These results shed some light on the question about the simultaneous development of the MMFs, the CP, and the repo markets, and whether the explosive growth in the financial assets of the MMFs also led to the development of the CP and the repo markets. Our results suggest that though their financial assets do move together in the long-run, it is only the MMFs that respond to any deviations, while the CP and the repo market do not participate in the error correction process.

The results are further reinforced by the multivariate Beveridge-Nelson decomposition where we find that the MMFs has the biggest cyclical component. This is not surprising since it is the MMFs that move to correct for any disequilibrium in the short-run. The estimated cycle from the cointegrating relationship also captures the huge swings in these markets in the period around the financial crisis. Our results are robust to the exclusion of the volatile financial crisis sample period. The evidence in the paper provides some rationale for the simultaneous development of the CP and the repo markets with the growing balance sheet of the MMFs, and the feedback mechanism that is present within the shadow banking system.

The remainder of this chapter is structured as follows: in section 1.2, we provide a background on the shadow banking system, MMFs, the CP, the repo markets and the data used in the empirical analysis. Section 1.3 provides methodological issues and the empirical evidence. Finally, the conclusions are presented in section 1.4.

2.2 Background and Data

2.2.1 The Shadow Banking System

Traditional banks (deposit banks) involve in maturity transformation where they use deposits to fund loans that are of long-term nature. The traditional banks receive deposit money which can be withdrawn at any time by the depositors. Further, these deposits are guaranteed by the Federal Deposit Insurance Corporation. From the loan transactions the banks earn interest income and the loan borrowers in turn promise to repay them. There are three main differences between the traditional banks and the shadow banks. First, when the shadow banks are faced with an emergency situation, such as investors wanting to redeem, they cannot borrow from the Federal Reserve. Second, they are not regulated like traditional banks and don't have access to deposit insurance from the FDIC. However, at the midst of financial crisis, the U.S. Treasury did extend support to the MMFs through the Treasury's Guarantee Program (TGP). While this program does act as a form of insurance to the MMFs, the principal motive of this program is to provide a temporary guarantee to protect the shareholders of MMFs.[4] Third, the traditional banks pay for deposit insurance and pass on a part of this cost along to the depositors.[5] In contrast, in case of the shadow banking system such insurance cost do not exist, and therefore, they have a cost advantage over traditional banks in that sense (Gorton et al., 2010).

Pozsar et al. (2010) define shadow banks to include finance companies, asset-backed commercial paper (ABCP) conduits, structured investment vehicles (SIVs), credit

[4] While it is true that the principle intent of such program is to temporarily safeguard the interests of MMFs stockholders, it is not completely inconceivable for investors to expect similar treatment in the future, often known as the problem of moral hazard.

[5] It is important to note that the extent to which the banks can pass on the cost of insurance to the depositors depends on the degree of elasticity that the banks face, with the remainder of the cost borne by the banks, like any other indirect taxes.

hedge funds, MMFs, securities lenders, limited-purpose finance companies (LPFCs), and government-sponsored enterprises (GSEs). Figure 1.1 presents the shadow banking system in the U.S. We can see that in the U.S. shadow banking system, the CP and the repo markets appear on the asset side and MMFs on the liability side. Investors bring their money to the shadow banking system and get shares from the MMFs or collateral from the securities lender. On the other side, the borrowers provide financial assets and collateral to the shadow banking system. Thus, the relationship between the lender and the borrower has an additional layer of complexity as compared to the traditional banks.

The unraveling of the financial system during the financial crisis also led to defaults in the short-term debt market linked to this asset class. Gorton et al. (2010) explain that the developments in the subprime market led to the collapse of the MMFs, the CP, and the repo markets, as well as the overall shadow banking system. As shown in Figure 1.2, the financial assets of the MMFs, the CP, and the repo markets grew exponentially before the financial crisis, but declined significantly during the financial crisis.

2.2.2 Money Market Funds

One of the main players in the U.S. shadow banking system is the MMFs. At the end 2013, the MMFs managed over $2.68 trillion in assets which is 16.72 percent of all the total mutual fund assets in the U.S., and 8.6 percent of the mutual fund assets worldwide.[6] Figure 1.2 presents the time-series behavior of the MMFs from 1985 to 2013. It shows the rapid growth in the MMFs in 1998-2008 period with only a short dip in the 2002-2005 period. While the industry has expanded and reached the peak of 3.76 trillion in October 2008, its financial assets had dropped to 2.59 trillion by the end of 2013.

Rule 2a-7 of the Investment Company Act (1940) regulates the MMFs in the U.S. Under this rule, the quality, maturity, and diversity of investments in the money market fund portfolios are defined. Short-term yield, liquidity, and stability cause the MMFs to become a pool of cash management vehicle for retail and institutional investors. Stable

[6]The data is collected from Investment Company Institute according to which the total financial asset of the MMFs is $2.7 trillion, whereas the total financial assets of mutual funds in the U.S. is $16.14 trillion, and the corresponding assets equal $31.38 trillion for the whole world.

price per share, $1.00 per share under standard industry practice, has caused the MMFs to become similar to bank deposits. However, unlike traditional banks, it does not explicitly have the Federal insurance. This characteristic causes the MMFs to be a low-risk investment asset which satisfies stability. Apart from stability, each investment should satisfy quality, diversification, and maturity, which leads the MMFs to invest in short-term, high credit quality, and well-diversified instruments. Under rule 2a-7, the MMFs could have potentially curtailed the spreading of risks before the financial crisis of 2007-2008. However, that become very limited in the stressful conditions that the markets faced in September 2008. Lehman's failure and uncertainty in the financial system led MMFs to face significantly high level of outflows. The huge outflows greatly inhibited the MMF's ability to maintain liquidity. The liquidity stress in turn made investors to transfer their assets from the prime MMFs to other secure funds. As a result of the stress in the market, the MMFs were unable to maintain a stable $1.00 net asset value, which is one of the important conditions required to prevent a run on the MMFs.

Given the importance of the MMFs, the academic literature has also started paying attention to its role in the financial system. Kacperczyk and Schnabl (2009) study the recent financial crisis by examining the risk-taking behavior of the MMFs. They show that the financial crisis has revealed that the MMFs have an incentive to take on risks, and are vulnerable to runs if the risks materialize. The MMFs which took more risks were more prone to runs. Duygan-Bump et al. (2013) consider one of the ways to respond to these kinds of risks. They used the difference-in-difference approach to illustrate the role of the ABCP money market fund liquidity facility (AMLF) during the financial crisis. Their findings highlight that the AMLF can help to stabilize asset outflows from the MMFs and also decrease asset-backed-commercial-paper yields. Schmidt et al. (2014) study the run on the MMFs during the period of September and October of 2008 at a daily frequency. They emphasize that the MMFs which promised higher yields and less liquid securities were taking more risk and faced runs. These studies show that the MMFs faced runs which played an important role during the financial crisis.

2.2.3 The Commercial Paper Market

The MMFs provide the biggest source of funding for the CP market. Investment in the CP market is also consistent with the mandate of the MMFs, as it satisfies one of the main requirements for MMFs of being a low-risk investment and has short-term maturity horizon. In the U.S., dealers and corporations are the main issuers of the CP. The issuers of CP finance their projects or increase their capital base and in return investors receive interest which is the difference between the purchase price and the face value of the CP. There are three types of investors in the CP market. Type one purchases the CP at issuance and holds them till maturity. Type two purchases the CP to trade in secondary markets. Type three investors prefer to purchase newly issued CP from the same issuer while their holding of the CP matures. There is a liquidity risk for which the issuers could not refinance maturing CP.

In the 1970s, the MMFs occupied a significant share in the overall mutual funds industry, which in turn became a big part of investments in the CP market. Inventory in CP led to the creation of asset-back commercial papers (ABCP). ABCP are CP which are backed by some underlying asset. Most studies that investigate the run on the financial system (traditional and shadow banking system) show that a shock to the financial system leads to increased risk (Ivashina and Scharfstein (2010), Campello et al. (2010), and Campello et al. (2011)). Covitz et al. (2009) consider run on ABCP market by using micro-level data. They find that the run on ABCP in 2007 is related to weaker liquidity support and lower ratings which in turn aggravated the macro-financial risks.

Anderson et al. (2009) explain the run on the CP market during the financial crisis. They show that the MMFs invested in the CP as they provided revenue at low risk before the financial crisis. However, the bankruptcy of the Lehman Brothers caused a run on the CP market, which in turn had adverse effects on the money market fund investments. Kacperczyk and Schnabl (2009) explain that there are three reasons for the collapse and run on the CP market namely, adverse selection, using other source of financing, and the MMFs. These findings suggest that the CP and the MMFs are related to each other. However, these studies do not explain how these two markets move together over different horizons, which is one of the main objectives of the current paper. While these papers provide good insights into the interlinked runs in the CP market and the MMFs, it is also important to recognize the potential connections with the repo market as it is another important source of financial intermediation in the shadow banking system.

2.2.4 The Repo Market

The CP and the repo markets are two important components of the shadow banking system, especially for the MMFs (as a main cash player in the shadow banking system). The repo agreements (or simply repo) are a form of the short-term funding facility, as they are simply the agreement of sale and future repurchase of a financial asset. This asset in most cases is Treasury securities, but over time it has changed, and other short-term debt instruments which were linked to the subprime mortgage are now a part of the financial asset over which repo are undertaken. Cash-rich financial market players such as the MMFs and securities lenders, lend to the borrowers and receive securities as collateral that are greater than the amount of the loan. This loan is repaid along with the interest rate, commonly known as the repo rate.[7]

Most of the research in the shadow banking system has examined one of these financial intermediaries separately. Schmidt et al. (2014), He and Xiong (2012), Gennaioli et al. (2013), and McCabe (2010) consider the role of the MMFs during the financial crisis and modeled runs in the MMFs. Parlatore Siritto (2015) presents a model to analyze the impact of the regulations on the shadow banking system. Kacperczyk and Schnabl (2013) explain the risk-taking behavior of MMFs during the financial crisis. Kacperczyk and Schnabl (2009), Duygan-Bump et al. (2013), and Anderson et al. (2009) study the role of CP market during the financial crisis. Krishnamurthy et al. (2014), Gorton et al. (2010),

[7] Gorton et al. (2010) define "Securitized Banking" as a combination of securitization and repo. Studying the 2008-2009 subprime housing market crisis, their findings suggest that changes in liquidity and risk of collateral in the repo market led to a run on the repo market. This is potentially one of the risk propagation mechanisms that played a role in financial crisis. Krishnamurthy et al. (2014) find that the repo market segments that were dependent upon the financing from the MMFs collapsed after the financial crisis of 2008. They showed that the repo market is a small portion that could not be the only reason for the collapse of the shadow banking system, but it is important to consider the repo markets as part of the short-term debt market. However, these findings do not support Gorton et al. (2010) view which hypothesized that the repo was one of the main reasons for the financial crisis.

and Copeland et al. (2010) model the run on the repo market. We argue that examining the role of these financial intermediaries separately may be an important objective in itself, but we also need to understand the dynamic relationship among these dominant players in the shadow banking system. Our paper tries to fill this gap by examining the long-run and the short-run relationship among the MMFs, the CP, and the repo markets.

2.2.5 Data

We use 28 years of quarterly data from 1985 to 2013 for the MMFs, the CP, and the repo markets. Data is obtained from the Board of Governors of the Federal Reserve System. For the MMFs, we collect the level of total financial assets. Figure 1.2 shows that the MMFs grew slowly until 1990, but registered significant expansion during the later half of the 1990s as well as in the 2005-2008 period. The size of this market was $2.47 trillion at the beginning of 2007 and in September of 2008 it reached the peak of around $3.76 trillion. Figure 1.2 reflects that the MMFs started becoming unattractive very quickly after the collapse of the Lehman Brothers in September 2008. At the end of 2013, total financial assets stood at $2.66 trillion, which was significantly lower than the peak reached during the period of financial crisis.

Very similar behavior can be found in the case of the CP market. At the beginning of 2007, CP were the largest U.S short-term debt instruments, but during the financial crisis of 2007-2008 the CP market faced significant stress. Figure 1.2 shows the boom and the bust in the outstanding CP. Until 2005, the total amount of outstanding CP was relatively stable. Between early 2005 and the summer of 2007, the amount of outstanding CP nearly doubled, reaching a peak of $2.10 trillion. However, with the onset of the financial crisis it started to decline and stood around $1.85 trillion in the third quarter of 2007. The collapse in the CP market happened before the decline in the financial assets of the MMFs.

The aggregate amount of repo funding provided to the shadow banking system (from MMFs) is also reported in Figure 1.2.[8] At the end of 2007, the total amount of repo stood at its peak around $605.90 billion, which started to decline with the failing of Lehman

[8] Data for repo markets has been obtained from the Flow of Funds Accounts that the Federal Reserve Board releases (Table Z.1) (Krishnamurthy et al., 2014).

Brothers. The evidence in figure 1.2 suggests that the collapse of MMFs and the repo occurred around the same time, while the collapse of CP market started one year prior to this time. Table 1.1 provides the descriptive statistics of the data. These initial statistics show that on an average the CP and the repo market together ($1.21 trillion) is about 80 percent of the MMFs average of $1.51 trillion. This provides a very preliminary evidence of the potentially strong interconnections that exists between the three markets. In terms of the overall fluctuations measured by the standard deviations, the findings presented in Table 1.1 suggests that repo market witnessed higher fluctuations as compared to the other two markets.

2.3 Dynamic Relationship in the Shadow Banking System

2.3.1 The Long-Run Relationship

The MMFs are one of the biggest players in the shadow banking system. The CP and the repo markets are the two most important avenues of investments for the MMFs. A significant portion financial asset of MMFs are channelized into the CP and the repo markets. This unique nature of interconnections between the three markets would have implications on the size and development of these markets. Thus, testing and studying the nature of long-run relationship between these markets would provide us with interesting insights into the operations of the shadow banking system.

In order to study the long-run cointegrating relationship, it is important to first test whether each variable passes the unit root test. In particular, the variables of the cointegration system need to be non-stationary in levels and stationary in their first differences. Table 1.2 summarizes the results of the unit root test. We find that the levels of MMFs, CP and repo markets contain a unit root, whereas the null hypothesis of the existence of unit root is rejected for the first difference form of these variables.

Let mmf, cp, and $repo$ represent the natural logs of the total financial assets of MMFs, CP, and repo markets respectively. Given these variables are non-stationary in levels, the following equation 1 presents the long-run relationship between the three variables:

$$mmf_t = \beta_0 + \beta_1 cp_t + \beta_2 repo_t + \epsilon_t \tag{2.1}$$

where, β_0, β_1, and β_2 are the coefficients of the constant, cp, and $repo$, respectively. If there exists a common long-run trend between mmf, cp, and $repo$ and they comove in the long-run, then the estimated cointegrating residual $\hat{\epsilon}_t = mmf_t - \hat{\beta}_0 - \hat{\beta}_1 cp_t - \hat{\beta}_2 repo_t$ should be stationary. To check for stationarity of estimated residuals the standard unit root test is applied. Here, the coefficients $(\beta_0, \beta_1, \beta_2)$ of equation 1.1 constitute the cointegrating vector of the system which reflects how the three markets move together in the long run.

One would expect that an increase in cp_t and $repo_t$ would have a positive impact on mmf_t. Consequently, both β_1 as well as β_2 are expected to have a positive sign. This is because in the shadow banking system, the CP and the repo markets are a part of the asset side, whereas the MMFs are on the liability side of the balance sheet of the system as a whole. At the same time, higher trading activity in the CP and the repo markets provides a perfect ground for expanding activity by the MMFs industry. Further, the relative size of β_1 and β_2 would provide the information about the relative influence of the CP and the repo markets on the MMF's activity.

To estimate the precise cointegrating relationship between the MMFs, the CP, and the repo markets, we adopt the Stock and Watson (1988) dynamic ordinary least squares (DOLS) methodology. Given the possibility of serial correlation in the error term, we use Newey-West heteroscedastic autocorrelation consistent standard errors. More specifically, the following DOLS is estimated with one lag selected based on the Schwartz criterion:

$$mmf_t = \beta_0 + \beta_1 cp_t + \beta_2 repo_t + \sum_{i=0}^{1} \Delta cp_{t-i} + \sum_{i=0}^{1} \Delta repo_{t-i} + e_t \tag{2.2}$$

Panel A in Table 1.3 shows the null hypothesis of the existence of unit root in the estimated cointegration residual $(\hat{\epsilon}_t)$ is rejected. Panel B and Panel C in Table 1.3 summarize the results of the cointegration from Johansen (1991) and Engle and Granger

(1987). Based on the Johansen test, there is at least one cointegrating vector between the MMFs, CP and the repo markets. Also, the results of the Engle-Granger test show the null hypothesis of unit root for the residual from the regression of the mmf on the $repo$ and cp is rejected, suggesting the existence of a cointegrating relationship between the three variables.

Table 1.4 presents the DOLS estimates for the 1985-2013 period in columns 2-3 along with the P-values. The results clearly show that all coefficients in the vector (β_0, β_1, β_2) which capture the cointegrating relationship are highly significant. This implies that MMFs, the CP and the repo markets share a statistical significant common long-term trend between them. Further, evidence in Table 1.4 reveals some interesting dynamics of the shadow banking system. Evidence suggests that for the 1985-2013 period, a one percent increase in the size of the CP market leads to an increase in the size of the MMFs by 0.49 percent in the long run. Whereas, the MMFs are estimated to expand in the long run by 0.59 percent for every one percent increase in the repo market. This means that in the shadow banking system, the MMFs share a stronger relationship with the repo market as compared to the CP market. However, contrasting behavior (as discussed separately in the section below) emerges once the influence of the recent financial crisis is excluded.

Based on these results one can conclude that any deviations from the long-run relationship between these three markets ($\hat{\epsilon}_t > 0$ or $\hat{\epsilon}_t < 0$), will induce a movement in at least one of these markets such that it will restore the shared long-run relationship. Figure 1.3 presents the estimated residuals obtained from the DOLS methodology. This figure shows how the short-term deviations in the cointegrated system have behaved over time. We find that right before the financial crisis the size of MMFs was below the long-term cointegrating trend but this was quickly corrected with the onset of crisis.

The presence of a common cointegrating trend between MMFs, CP and repo markets can have important policy implications. For example, the impact of measures like the Treasury's Guarantee Program for MMFs can potentially extend beyond the MMFs market. The explicit interconnections estimated in this paper allows us to understand the extent of propagating mechanism between the policy action and the three most important markets of the shadow banking system. At the same time, the results also provide a cautionary note to the potential problems of moral hazard that is often discussed by the policy makers.

2.3.2 The Short-Run Relationship

The established long-term relationship in the above section suggests that at least one of the three variables would error-correct for any short-term disequilibrium. The Engel-Granger representation theorem provides the VECM representation of the integrated system as follows:

$$\triangle Y_t = \nu + \Gamma(L)\triangle Y_{t-1} + \alpha\hat{\beta}' Y_{t-1} + \epsilon_t \tag{2.3}$$

where, $\Delta Y_t = (\Delta mmf_t, \Delta cp_t, \Delta repo_t)'$ represents the vector of the first differences of the three variables and $\Gamma(L)$ represents a finite-order distributed lag operator. The vector of adjustment parameters is given by $\alpha = (\alpha^{mmf}, \alpha^{cp}, \alpha^{repo})'$. More specifically, the number of lags is chosen based on the SBIC and then the following system of equations is estimated:

$$\Delta mmf_t = \gamma_0 + \gamma_{11}^{mmf}\Delta mmf_{t-1} + \gamma_{12}^{cp}\Delta cp_{t-1} + \gamma_{13}^{repo}\Delta repo_{t-1} + \alpha^{mmf}\hat{\beta}' Y_{t-1} + e_{mmf,t} \tag{2.4}$$

$$\Delta cp_t = \gamma_0 + \gamma_{21}^{mmf}\Delta mmf_{t-1} + \gamma_{22}^{cp}\Delta cp_{t-1} + \gamma_{23}^{repo}\Delta repo_{t-1} + \alpha^{cp}\hat{\beta}' Y_{t-1} + e_{cp,t} \tag{2.5}$$

$$\Delta repo_t = \gamma_0 + \gamma_{31}^{mmf}\Delta mmf_{t-1} + \gamma_{32}^{cp}\Delta cp_{t-1} + \gamma_{33}^{repo}\Delta repo_{t-1} + \alpha^{repo}\hat{\beta}' Y_{t-1} + e_{repo,t} \tag{2.6}$$

The last period disequilibrium is presented as $\hat{\beta}' Y_{t-1} = mmf_{t-1} - \hat{\beta}_0 - \hat{\beta}_1 cp_{t-1} - \hat{\beta}_2 repo_{t-1}$. The statistical significance of coefficients ($\alpha' s$) indicate that the corresponding variable corrects in the current period in response to the previous period's shock which disturbed the long-term equilibrium. If at least one of the $\alpha' s$ is significantly different from zero then we can conclude that Y_t is cointegrated.

The VECM results are presented in Table 1.5 (columns 2-4) for the 1985-2013 period. The results show that α^{mmf} is statistically significant, whereas α^{cp} and α^{repo} are not. It means any deviation of the CP and the repo markets from the shared long-run trend will be corrected by the MMFs, while the CP and the repo markets do not participate in the error correction process. Further, the speed of adjustment for the MMFs is -0.06 which implies a half-life of little less than three years. Thus, while there is a shared long-run relationship between the MMFs, the CP and the repo markets, the error-correction is only done by the MMFs and it is a fairly sluggish adjustment process. The slow adjustment is consistent with what international finance and finance researchers have found for the exchange rate and stock market. For example, researchers have found that even though dividend and stock prices may tend to move together in the long-run, the speed of error-correction is usually very sluggish. The purchasing power parity literature also reports similar findings for the speed of error correction in case of exchange rates.[9]

Evidence in Table 1.5 (columns 2-4) also suggests that lagged values of change in MMFs have a positive impact on the current growth rate in both the CP and the repo markets. However, the reverse is not necessarily the case. The current value of the MMFs is positively affected by the lagged values of the CP and the repo markets, the coefficients are not statistically significant. The intuition for such a behavior could lie in the dynamics of the shadow banking system. Since MMFs are one of the biggest investors in the CP and the repo markets, growth in the MMFs industry would provide a higher incentive to the issuers of CP and repo securities. The growth in the MMFs thus provides a positive impetus to the other two markets. Further, the positive impact of MMFs growth is stronger on the repo market (0.72) as compared to the CP market (0.27).

Our findings show that if there are any short-term fluctuations in the shadow banking system, the MMFs correct it to restore the equilibrium that is shared with the CP and the repo markets. These results also match the simultaneous decline in the CP market and MMFs in 2007, which enabled the convergence back to the shared long-run path. From the figures 2 and 3 evidence suggests that the CP market collapsed one year before the money market collapsed.

2.3.3 Beveridge-Nelson Decomposition

Given that there exists a cointegrating relationship between the MMFs, the CP and the repo markets, we can use this information to perform a trend-cycle decomposition. This exercise will further help us understand the trend and cyclical component in all the three

[9] For example, see Frankel and Rose (1996) and Cochrane (1994).

variables that are a part of one cointegrated system. In particular, it allows us to measure the extent of movement in these variables that are permanent and transitory in nature. Furthermore, it also reinforces the results found in the above sections.

The cointegration results suggest that among the three markets, it is the MMFs that error corrects, whereas the CP and the repo markets do not. If that is the case then the cyclical component of the MMFs should be able to identify these dynamics between the three markets. We adopt a state-space approach of the Beveridge and Nelson (1981) to estimate the permanent and transitory components of an integrated time series which Cochrane (1994) and Morley (2002) provided. Based on the equations 1.4, 1.5 and 1.6, we define the Beveridge-Nelson (BN) decomposition as:

$$\begin{bmatrix} \Delta mmf_t - \mu \\ \Delta cp_t - \mu \\ \Delta repo_t - \mu \\ \hat{\beta}' Y_t \end{bmatrix} = \begin{bmatrix} \gamma_{11}^{mmf} & \gamma_{12}^{cp} & \gamma_{13}^{repo} & \alpha^{mmf} \\ \gamma_{21}^{mmf} & \gamma_{22}^{cp} & \gamma_{23}^{repo} & \alpha^{cp} \\ \gamma_{31}^{mmf} & \gamma_{32}^{cp} & \gamma_{33}^{repo} & \alpha^{repo} \\ \gamma_{41}^{mmf} & \gamma_{42}^{cp} & \gamma_{43}^{repo} & \alpha \end{bmatrix} \begin{bmatrix} \Delta mmf_{t-1} \\ \Delta cp_{t-1} \\ \Delta repo_{t-1} \\ \hat{\beta}' Y_{t-1} \end{bmatrix} + \begin{bmatrix} e_{mmf,t} \\ e_{cp,t} \\ e_{repo,t} \\ e_{Y,t} \end{bmatrix} \tag{2.7}$$

In this model, $\Delta mmf_t - \mu$, $\Delta cp_t - \mu$, and $\Delta repo_t - \mu$ are demeaned mmf, cp and $repo$ and $\gamma_{41}^{mmf} = \gamma_{11}^{mmf} - \beta\gamma_{21}^{mmf} - \beta\gamma_{31}^{mmf}$, $\gamma_{42}^{cp} = \gamma_{12}^{cp} - \beta\gamma_{22}^{cp} - \beta\gamma_{32}^{cp}$, $\gamma_{43}^{repo} = \gamma_{13}^{repo} - \beta\gamma_{23}^{repo} - \beta\gamma_{33}^{repo}$, $\alpha = 1 - \alpha^{mmf} - \alpha^{cp} - \alpha^{repo}$, and $e_{Y,t} = e_{mmf,t} - e_{cp,t} - e_{repo,t}$.

The stated model can be compactly written as:

$$\Delta X_t = F \Delta X_{t-1} + \nu_t \tag{2.8}$$

The BN cycle is $-F(I-F)\Delta X_t$ and the trend component is $X_t + -F(I-F)\Delta X_t$. Figures 1.4 and 1.5 show the results from BN decomposition for the MMFs, the CP and the repo markets. Figure 1.4 shows the trend and actual for these variables, whereas the cyclical component for each variable is presented in figure 1.5.

Figure 1.4 shows that for both the markets (CP and repo) the trend and the actual significantly overlaps as compared to the overlap of the trend and the actual of the MMFs. This is true particularly for the period around the crisis. The difference between the trend and the actual (Fig. 1.5) shows that the cyclical component in case of the CP and the repo market is fairly small as compared to the MMFs cycles. This further supports the evidence found earlier that the MMFs adjust for any deviations caused to the long-run relationship. Between the three markets, the actual behavior of the repo market is the most closest to its trend line (Fig. 1.4). Further, the MMFs cycle shows some evidence of sustained deviations from the zero-mean line. This corroborates with the slow adjustment process found for the MMFs in the cointegrated VAR model. Thus, the overall results are consistent with the evidence found from the cointegration exercise.

2.3.4 The Role of the Recent Financial Crisis

Given the extraordinary influence of the recent financial crisis on the shadow banking system, it is important to check for robustness of the results, and also understand the role of crisis.[10] Are the results robust to the exclusion of the crisis period or are they driven by this extraordinary event? At the same time, this exercise also helps us understand the change in the dynamics of the shadow banking system. To achieve this objective, we perform the above exercise for the sub-sample that runs from the first quarter of 1985 through the second quarter of 2007.[11]

Table 1.4 (columns 4-5) presents the DOLS estimates of the co-integrating vector along with the associated P-values. The results show that the cointegrating relationship between the MMFs, the CP and the repo markets is robust to the exclusion of the effects of the recent financial crisis. The cointegrating vector remains statistically significant. However, it is interesting to find that the magnitude of the DOLS coefficients for the CP and the repo markets differ for the sub-sample as compared to the full sample estimates. For the full sample period, we noted that the repo market is slightly more important than the CP market in their long-term relationship with the MMFs. In contrast, if we exclude the period of financial crisis the elasticity of the response of MMFs to the CP and the repo markets is 0.98 and 0.26 respectively. Thus, the influence of CP market on the MMFs in the normal

[10] We choose to the second quarter of 2007 when BNP Paribas terminated withdrawals from hedge funds.

[11] It can also be argued that the dynamic relationship among these variables may have also changed in 1994 given the changes in the MMF industry around that time period. We check whether there was a break in the cointegration vector in 1994 using Hanson (2002) method and we do not find a break in the cointegration vector in 1994.

periods is nearly four times as compared to the repo market's influence on the MMFs. This shows the degree of portfolio reshuffling witnessed in the shadow banking industry from the CP market to the repo market in the crisis period.

Figure 1.6 shows the behavior of the estimated cointegrating residual for the 1985-2007 sample period. Evidence suggests that in the late 1980s the MMFs operated below the long-term cointegrating trend but by early 1990s it quickly recovered. In contrast, the MMFs grew above the trend in the early 2000s but nose-dived in 2005. This behavior is qualitatively similar to the results obtained when the crisis period is included in our estimation process (Fig. 1.3); though perhaps the adjustment process is relatively smoother when the crisis period is excluded. This evidence confirms that the estimated cointegrating residual is robust to the financial crisis.

For the short-term error correction model, the main results are both qualitatively as well as quantitatively robust to the exclusion of the crisis period. These results of the VECM are presented in columns 4-5 of Table 1.5. We find that, again only the adjustment coefficient of the MMFs (α^{mmf}) is statistically significant. While the CP and the repo markets do not participate in the error correction process, since both α^{cp} and α^{repo} are insignificant. Furthermore, even quantitatively, the speed of adjustment done by the MMFs remains unchanged at -0.06, same as the full sample period estimate.

From Table 1.5, it is equally interesting to find the changing role of the three markets when we compare the full sample period (columns 2-3) with the sub-sample period (columns 4-5) that excludes the crisis. As discussed before, in the case of the full sample period the positive impact of lagged MMFs growth feeds into the expansion of the CP and the repo market. However, for the 1985-2007 sample period, while lagged MMFs growth still has a positive impact (with nearly the same magnitude of 0.7) on the repo market growth, its impact on the CP market growth is statistically no different than zero. In fact, there is evidence that growth in the CP market in the past quarter fosters growth in the MMFs in the current quarter. After the financial crisis, the repo market played as much of a role as the CP market did.

Overall, the results show that the co-integrating vector as well as the error correcting coefficients remain robust and do not change with the exclusion of the financial crisis period. The robustness test results also highlight the changing dynamics that occurred in the shadow banking industry over time, particularly in and around the period of financial crisis.

We also use information from the cointegration witnessed in the 1985-2007 period to decompose the series into the BN trend and cycle. The results are presented in figures 1.7 and 1.8. These graphs show that there is no qualitative change in the trend-cycle of each variable for the sample that excludes the crisis period (Fig. 1.7-1.8) as compared to the full sample (Fig. 1.4-1.5). The cyclical component of the MMFs shows evidence of periods of sustained deviations from the zero-mean line. This is consistent with the slow error correction process of the MMFs in the VECM. Quantitatively, we find that right before the crisis the cyclical component of the MMFs (Fig. 1.8) is slightly larger than the full sample estimates of the MMFs cycle (Fig. 1.5). This evidence brings forth the extent of stress that was faced in the shadow banking system due to the financial crisis.

2.4 Conclusion

There is a consensus on the important role played by the financial intermediaries that are a part of the shadow banking system during the last recession. The money market funds, commercial papers, and repurchase agreements are three main players at the center of the shadow banking system. In this study, we examine the long-run and the short-run relationship among these markets by using a time-series econometric approach. Our results show that the money market funds, the commercial paper and the repo markets move together in the long-run. Further, any deviation in the shared long-run equilibrium forces the money market funds to error-correct to restore the equilibrium relationship on this long-run path. The results suggest that financial assets of money markets in the short-run do respond to dynamic movements in the commercial papers and the repo market. This provides some rationale for the simultaneous growth of the commercial papers and the repo market with the growing balance sheet of the money market funds.

Further, we use the information from the cointegrating relationship to estimate the permanent and transitory components of an integrated time series. Our results from the trend-cycle decomposition show that the cycle of the money market funds is relatively greater than the cyclical component of the other two variables. This supports the results from the error correction model. To examine whether our results are sensitive to the financial crisis, we undertake the same analysis by excluding the period of recent financial crisis and compare them with the whole sample results. We find that our results are robust and do not change when we exclude the recent financial crisis. The robustness check also brings forth the changing role of the commercial papers and the repo markets in the crisis era of the shadow banking system.

Table 2.1: Descriptive Statistics

Variable	Mean	Median	Max	Min	Std. Dev.
MMF	1521.2	1507.00	3757.00	242.00	1013.20
CP	990.00	1018.10	2109.00	247.60	479.60
Repo	221.00	142.00	605.00	17.85	180.00

Note: The table provides descriptive statistics for the money market funds (MMFs), commercial paper (CP) and repurchase agreements (repo) in billion of dollars.

Table 2.2: Unit Root Test

Variable	PP P-Value
MMF	0.98
CP	0.97
Repo	0.72
ΔMMF	0.01
ΔCP	0.01
$\Delta Repo$	0.01

Note: Δ denotes the first difference. PP denotes the Phillip Perron test

Table 2.3: Cointegration Test

Panel A : Cointegration results from the DOLS approach

	Full sample (1985:Q1 to 2013:Q4)	Sub-sample (1985:Q1 to 2007:Q2)
	PP P-Value	PP P-Value
Residual	0.00	0.00

Panel B : Cointegration results from Engle and Granger (1987)

	Full sample (1985:Q1 to 2013:Q4)	Sub-sample (1985:Q1 to 2007:Q2)
	PP P-Value	PP P-Value
Residual	0.00	0.08

Panel C : Cointegration results from Johansen (1991)

	Full sample (1985:Q1 to 2013:Q4)		Sub-sample (1985:Q1 to 2007:Q2)	
	Number of Cointegration Vectors		Number of Cointegration Vectors	
	None	At most 1	None	At most 1
Eigenvalue	0.23	0.04	0.21	0.13
Trace statistic	37.73	7.43	34.13	12.81
0.05 critical value	29.79	15.49	29.79	15.49
P-Value	**0.00**	0.52	**0.01**	0.12

Note: This table represents the cointegration results for the full sample as well as the small sample. Panel A reports the estimates of the unit root for the residual of DOLS. Panel B and C show the estimates from Johansen(1991) also Engle and Granger(1987). PP denotes the Phillip Perron test.

Table 2.4: The DOLS estimate of the Co-integrating Vector

	Full sample (1985:Q1 to 2013:Q4)		Sub-sample (1985:Q1 to 2007:Q2)	
Coefficient	Value	P-Value	Value	P-Value
β_0	**3.42**	0.00	**4.02**	0.00
β_1	**0.49**	0.00	**0.98**	0.00
β_2	**0.59**	0.00	**0.26**	0.00

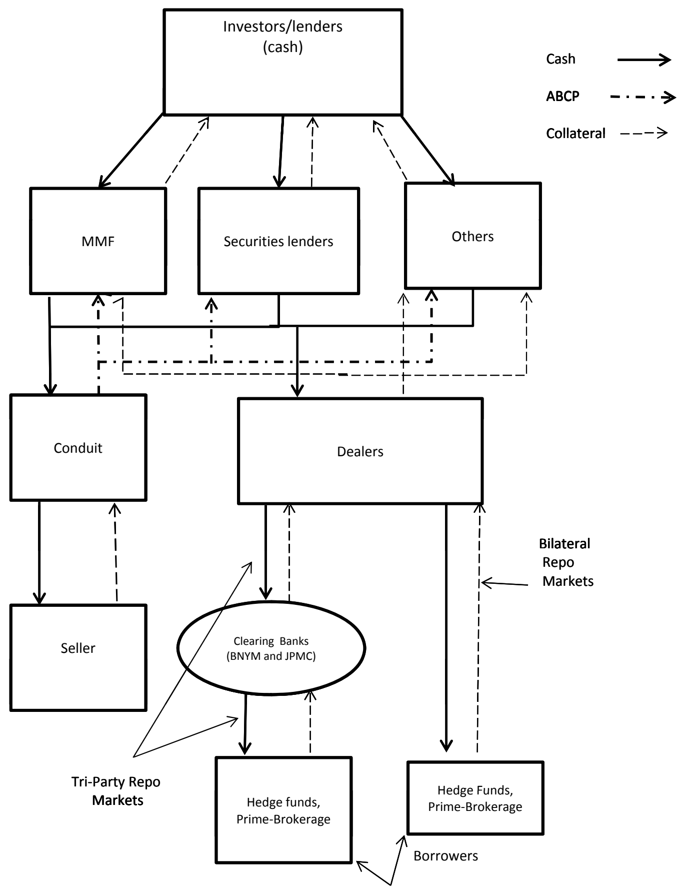
Note: The table reports DOLS estimates for the full sample as well as for the sub-sample which excludes the period of crisis.

Table 2.5: Estimates from the VECM model

	Full sample (1985:Q1 to 2013:Q4)			Sub-sample (1985:Q1 to 2007:Q2)		
Dependent Variable	Δmmf coefficient	Δcp coefficient	$\Delta Repo$ coefficient	Δmmf coefficient	Δcp coefficient	$\Delta Repo$ coefficient
Δmmf_{t-1}	0.49	0.27	0.72	0.38	0.07	0.74
	(0.00)	(0.05)	(0.00)	(0.00)	(0.29)	(0.00)
Δcp_{t-1}	0.07	0.14	0.18	0.33	0.77	0.31
	(0.18)	(0.14)	(0.11)	(0.00)	(0.00)	(0.23)
$\Delta repo_{t-1}$	0.02	-0.06	-0.25	0.01	-0.05	-0.31
	(0.53)	(0.36)	(0.00)	(0.73)	(.08)	(0.00)
$\hat{\beta}' Y_{t-1}$	**-0.06**	-0.01	0.06	**-0.06**	0.01	0.09
	(0.01)	(0.79)	(0.20)	(0.02)	(0.53)	(0.14)
R^2	0.41	0.07	0.21	0.42	0.57	0.18

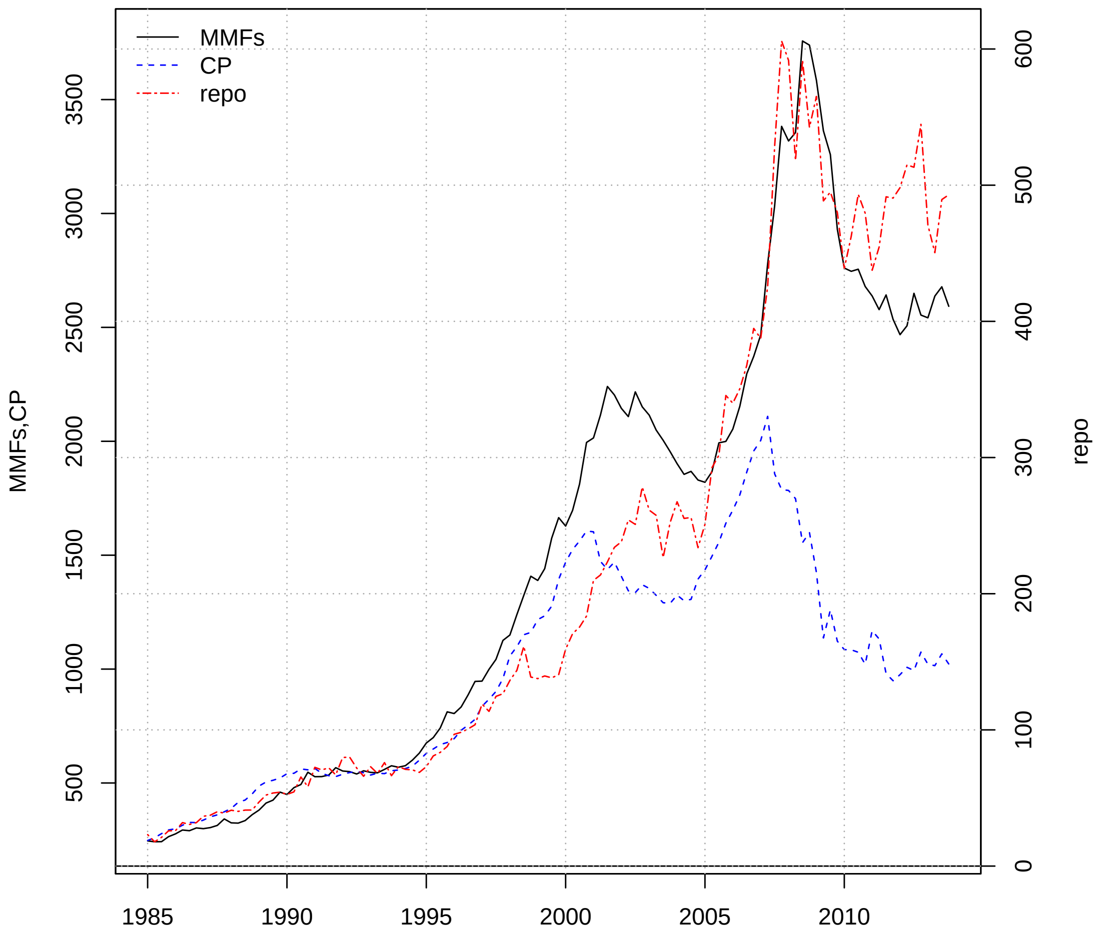
Note: The table reports the estimates (and the associated P-values) from the VECM for the full sample as well as for the sub-sample which excludes the period of crisis. Second last row shows the adjustment coefficient of the lagged value of the estimated co-integrating residual.

Figure 2.1: The Shadow Banking System



Sources: Krishnamurthy et al. (2014) and Copeland et al. (2014).
This figure presents a broader outline of the shadow banking system. The money market funds and Securities lender and others (Hedge funds etc.) receive cash from investors and in return pay a share of the money market funds ($1 NAV) or securities to the lender. Their cash provides funds for commercial papers or goes to the repurchase agreements market and in return receives asset back securities. Their findings can go to the dealer or the conduit. If they go to the Conduit for special purpose they will receive a financial asset which is called ABCP. If they go to the dealer, it can provide funds for the Hedge funds or Prime-Brokerage which called repurchase agreements (repo). The repo between dealers and hedge fund or prime-brokerage without clearing banks are bilateral repo. The repo between the hedge funds or prime-brokerage when there are clearing banks (BNYM or JPMC) are Tri-Party repo.

Figure 2.2: Financial asset of the MMFs, the CP, and the Repo markets



Notes: The graph shows the volume (levels) of financial assets of the money market funds, the commercial paper and the repo market in billion of dollars for the 1985-2013 period.

Figure 2.3: Residual from the DOLS (Full sample - 1985-2014)

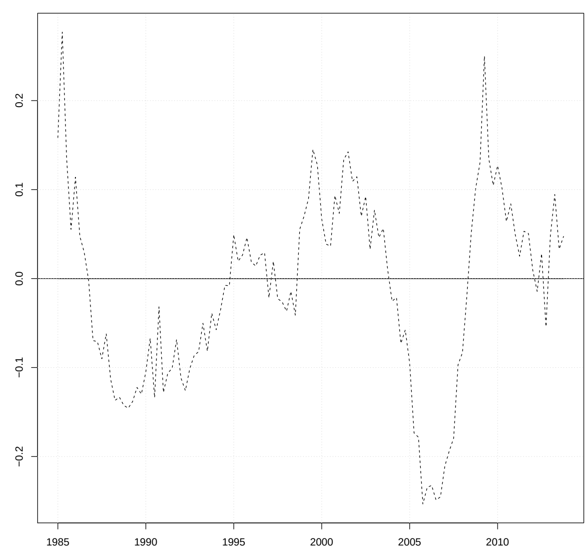
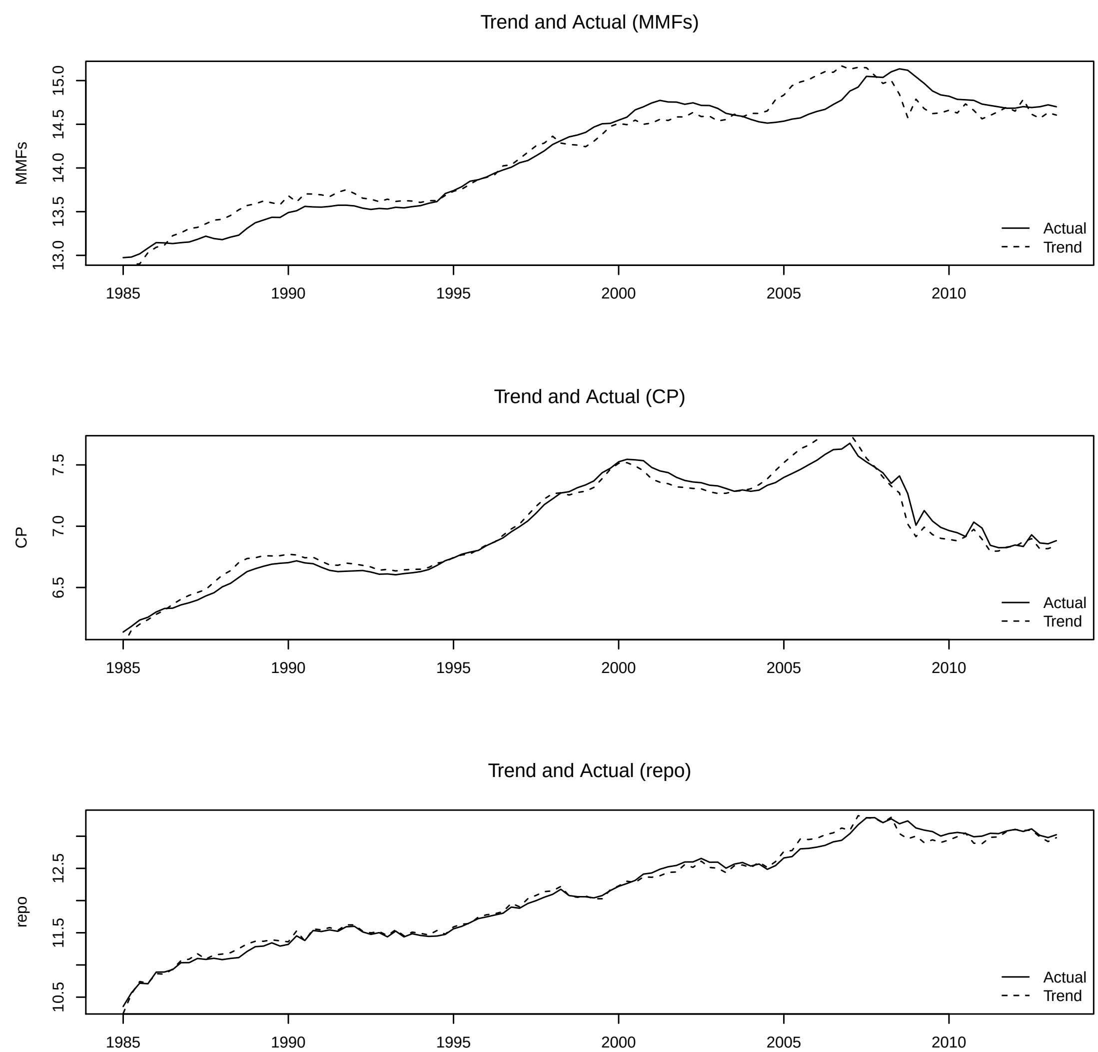
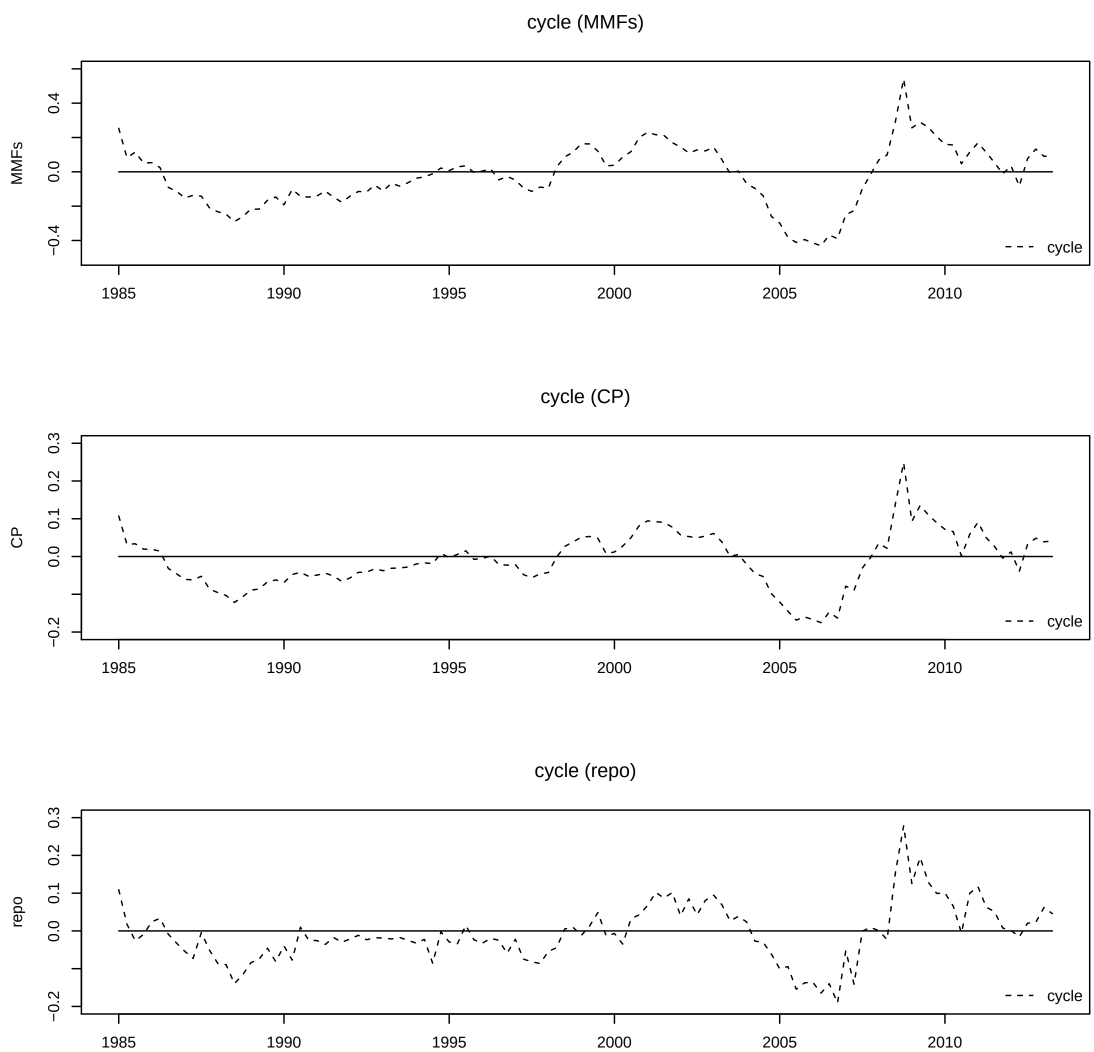


Figure 2.4: Estimated Trend from the BN decomposition



Notes: The graphs present the trend and actuals of financial assets of the MMFs, the CP and the Repo markets for the period 1985-2013.

Figure 2.5: Estimated Cycle from the BN decomposition



Notes: The graphs present the cycle of financial assets of the MMFs, the CP and the Repo markets for the period 1985-2013.

Figure 2.6: Residual from the DOLS (Sub-sample - 1985-2007)

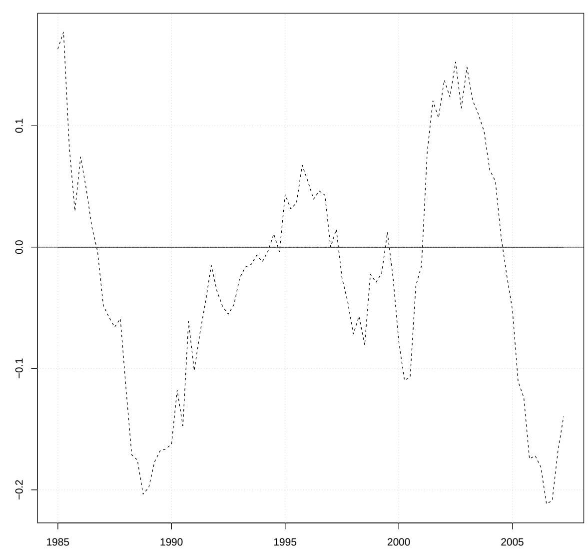
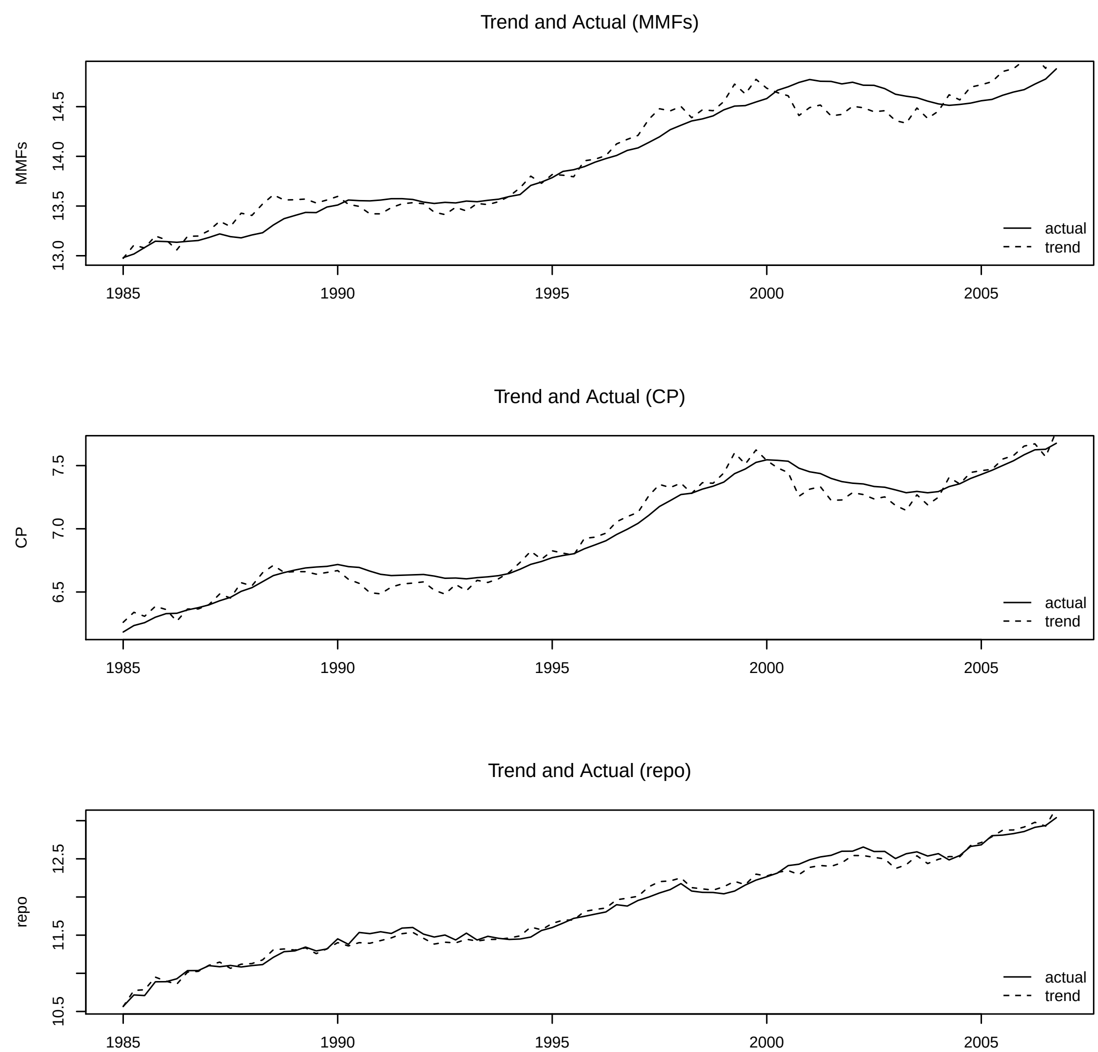
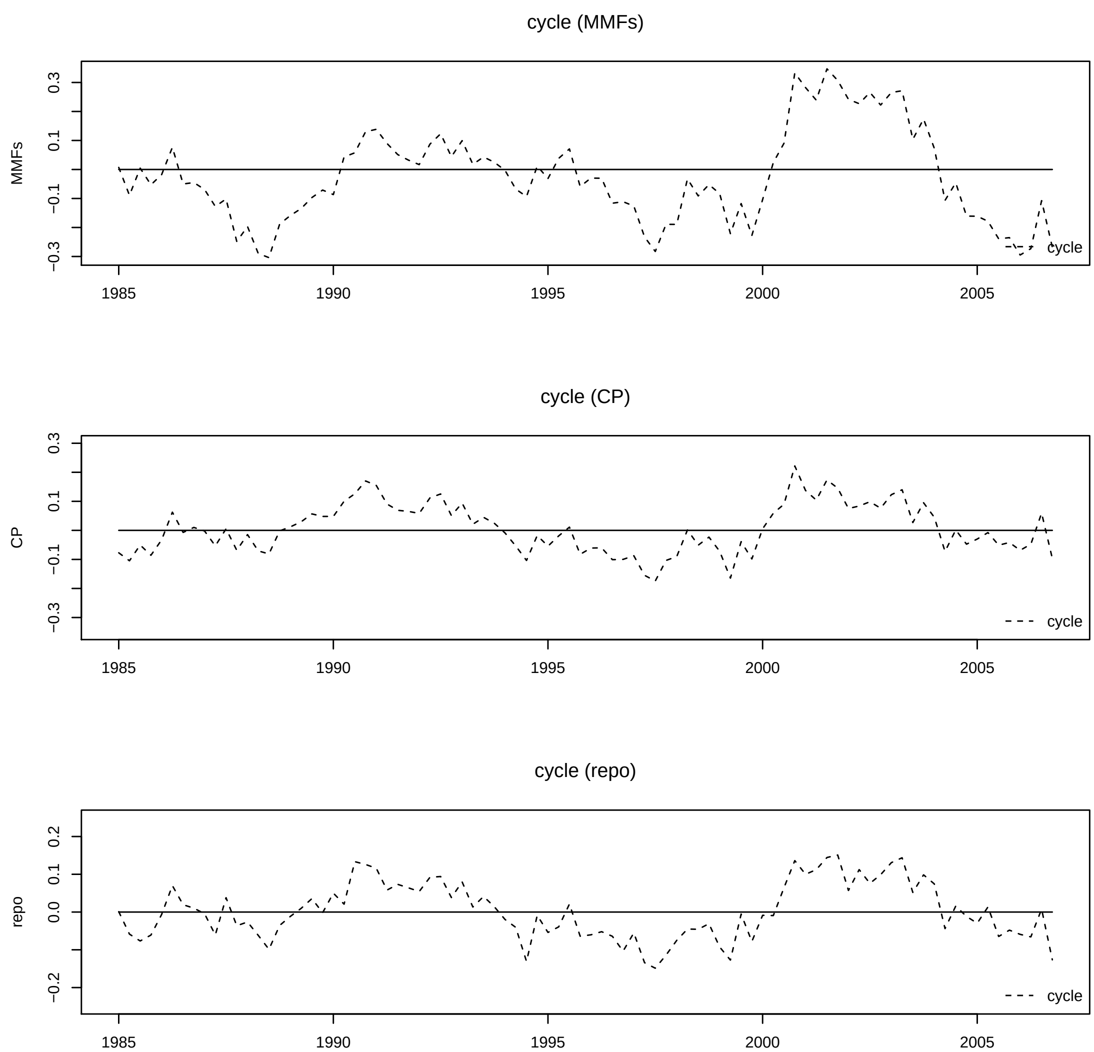


Figure 2.7: Estimated Trend from the BN decomposition (excluding crisis)



Notes: The graphs show the estimated BN trend for financial assets of the MMFs, the CP and the Repo markets for the period excluding the recent crisis 1985 to 2007.

Figure 2.8: Estimated Cycle from the BN decomposition (excluding crisis)



Notes: The graphs show the estimated BN cycle for financial assets of the MMFs, the CP and the Repo markets for the period excluding the recent crisis 1985 to 2007.

Chapter 3

The Effect of House Prices on Employment: Evidence from Agnostic Identification

3.1 Introduction

There is a consensus about the role of the housing market in causing and exacerbating the recent financial crisis. The big decline in housing prices was followed by a significant decline in real economic activity. The academic research has also started paying more attention to the relationship between the housing market and the broader economy for the last two decades. One strand of literature has focused on the relationship between house prices and macroeconomy expenditure by examining the net worth channel of housing. The net worth channel can either work directly through the wealth effect or through the indirect collateral effect. (Hurst and Stafford (2004), Case et al. (2005), Campbell and Cocco (2007), and Attanasio et al. (2009))

In a series of recent widely cited work, Mian et al. (2013) and Mian and Sufi (2014) show that this housing net worth channel has significant impact on employment. This study was motivated by a significant drop in employment during the financial crisis of 2009 in counties that also witnessed a big drop in house prices. Mian and Sufi (2014) argue that one of the predictions of housing net worth channel is the differential response of nontradable versus tradable employment across U.S. counties. The underlying idea is that non-tradable employment relies heavily on local demand, whereas tradable employment depends on national or global demand. Therefore if there is a shock to house price, it will translate into a bigger impact on local non-tradable employment. Mian and Sufi (2014) found that job losses in the non-tradable sector between 2007 and 2009 were significantly higher in counties with a large decline in housing net worth. Specifically, they found that a 10 percentage point decline in housing net worth is associated with a 3.7 percentage point decline in non-tradable employment.

In this paper we provide time-series evidence on the differential impact of housing price on non-tradable employment and tradable employment. Mian and Sufi (2014) sample period focused on the period of housing bust and its impact on tradable and non-tradable employment. Even though the housing bust period is of significant interest, it is also very important to examine the impact of housing market boom that preceded the bust. In particular, we use monthly data on tradable and non-tradable employment for 45 states for the time period 2001-2014 to perform our study. Moreover, unlike cross-sectional studies, the use of time-series data also allows us to examine the dynamic impact of house price shock on employment. In particular, our approach allows us to examine how persistent are the responses of the tradable and non-tradable employment to house price shocks and how much is the contribution of house price shocks in explaining the variation of tradable and non-tradable employment variation at different forecast horizons? One of the important policy questions in the immediate aftermath of the financial crisis was the jobless recovery that took place in the U.S. and whether the housing market crash has any role in it. Examining the persistence of the response of employment to house price shocks also helps us in understanding the role of house price shocks in the jobless recovery that took place in the U.S. after the financial crisis.

To examine the relationship between house prices and employment, we use a multivariate structural VAR with sign restrictions proposed by Uhlig (2005). This approach allows us to be agnostic about the impact of house price shock on employment and only imposes sign restrictions on other variables in the VAR system for a certain period. No restrictions are placed on the response of the tradable and non-tradable employment to house price shocks. Our baseline VAR includes building permits, share of non-performing loans in total loans, income and employment for all the states in our sample. We assume that a positive shock to house does not lead to a decline in new building permits, income and an increase in share of non-performing loans for the next 12 months. We impose no restriction on the impact of house price shock on tradable and non-tradable employment and therefore are agnostic about the impact of house price shock on these variables. The estimation of the structural VAR is done by using Bayesian approach via the Markov Chain Monte Carlo(MCMC) algorithm. In particular, we use the Penalty Function Approach to estimate the impulse responses.

Our results show that both tradable and non-tradable employment in all the states respond significantly to house price shock. In particular, we find that a positive shock to house price leads to a rise in tradable and non-tradable employment in all the states and this increase is highly persistent and in many states the effect persists for 4-5 years. Similar to the findings of Mian and Sufi (2014), we find that non-tradable employment on average responds more than tradable employment in 28 out of 45 states. The states with higher response of non-tradable employment to house price shocks are also the states with higher volatility in house prices. Not surprisingly, we find substantial heterogeneity in the magnitude and the duration of the responses across different states. For example, one standard deviation shock to house prices leads to a maximum annual response in non-tradable employment of 14.4% in Nevada, whereas the corresponding median estimate is 2.4% in case of New Jersey. We also find that the states with higher response of non-tradable employment to house price shocks are also the states with higher degree of correlation between real personal consumption expenditure and house prices. This suggests that net worth channel via wealth effect does play a role in the differential response of non-tradable employment to house price changes. Our results are also robust to alternate method of identification as proposed by Fry and Pagan (2011) [1].

The rest of the chapter is structured as follows. Section 2.2 briefly discusses the related literature. Section 2.3 introduces the methodology and model. Section 2.4 discusses the data. The results checks for robustness are presented in Section 2.5. Section 2.6 concludes.

[1] Median Target Approach

3.2 Literature Review

This paper builds on two strands of literature. We use the developments in the structural VAR literature to examine the impact of house price shocks on employment across different states. The literature on the relationship between the housing market and the macroeconomy has exploded after the financial crisis. The interest in the housing market's impact on macroeconomy was driven by the behavior of consumption during the recession of 2000-01, when the big decline in stock market wealth did not lead to a substantial decline in consumption. One hypothesis that was proposed by Alan Greenspan which found support in the academic literature was that the wealth effect arising out of the housing market is bigger than the wealth effect arising out of stock market wealth.(Case et al. (2005), Hurst and Stafford (2004), Kishor (2007), Campbell and Cocco (2007), Cooper (2009), Kermani (2012)). Therefore the rising house wealth in the early part of 2000 neutralized the impact of the big decline in stock market wealth and also decline in personal disposable income during recession on consumption.

The financial crisis of 2008-09 renewed the interest of policymakers and researchers in the dynamic relationship between the housing market and macroeconomy. Mian and Sufi (2008, 2010, 2011) in a series of papers show the role of the housing market on the fundamentals, by focusing on the financial crisis of 2007-2008.[2] Mian et al. (2013) consider the role of the large collapse of the housing market on household spending. Their results show households who live in poor and more levered neighborhoods have a significantly higher marginal propensity to consume therefore they experience greater wealth losses when housing prices collapse and a much bigger decline in consumption during 2006 to 2009.[3]

Our paper is closely related to Mian and Sufi (2014) who find that substantial drop in employment in the U.S. during 2007-2009 can be partly explained by the changes in

[2] Mian and Sufi (2008) consider the role of mortgage credit expansion on default. They show that during 2002-2005 increase in mortgage credit was followed by an increase in default. Mian and Sufi (2010) study the role of borrowing against increase in home equity. Their results show decrease in the house price from 2002 to 2006 led an increase in household leverage and linked to the 2007 to 2009 economic recession. Mian and Sufi (2011) show increase in leverage causes sharp decline in consumption during 2002-2006.

[3] They also show these households face a larger reduction in credit limits and credit scores during 2006-2009.

the housing net worth. In particular, they also found that counties that witnessed a larger decline in housing net worth also witnessed a larger decline in non-tradable employment than tradable employment. The argument proposed in favor of differential response of non-tradable versus tradable employment is that non-tradable employment relies heavily on local demand, whereas tradable employment relies more broadly on national or even gloabl demand. Therefore a natural prediction of the housing net worth channel is that while the change in non-tradable employment should be positively correlated with the change in housing net worth, while the change in tradable employment should not be as strongly positively correlated.

We examine the relationship between house prices and employment through the lens of time-series methods. For this purpose, we use recently made available time-series data at two-digit industry level for 45 different states. We follow Mian and Sufi (2014) definition of tradable and non-tradable employment across different industries. To do so, we employ a multivariate structural VAR to examine the impact of house price shocks on tradable and non-tradable employment. The literature on structural VAR is vast [4](Kilian, 2011; Fry and Pagan, 2011). One of the problems in the VAR literature is the identification of structural shocks as the conventional Cholesky decomposition of the VAR system may be sensitive to the ordering of variables. The shocks emanating from a conventional VAR method also lacks economic interpretation. There are several ways to get around the problem of identification in reduced form VAR models. For example, Blachard and Quah (1989) apply the long run identification to explain the fluctuations in GNP and unemployment, while Gali (1992) uses the short-run identification to examine whether the IS-LM model fit the postwar US data. Another approach for identification of shocks is the sign restriction method that has recently become very popular.[5]

In this paper, we use a method based on agnostic identification due to Uhlig (2005). He uses the informal identification to impose the sign on the impulse responses of prices,

[4] The SVAR models have been used to address the effect of monetary policy, supply and demand shocks, the effect of technology shocks, and the exchange rate shocks. (Bernanke and Mihov (1998), Christiano et al. (1997) ,Christiano et al. (1999), Faust (1998),Sanchez (2010), Altig and Nosal (2002),Peersman and Straub (2009),Francis et al. (2005),Scholl and Uhlig (2008), Farrant and Peersman (2006))

[5] Faust (1998), Uhlig (2005), Canova and De Nicolo (2002), Fujita (2011), Dungey and Fry (2009), Sanchez (2010)

non-borrowed reserves, and then, captures the effect of monetary policy shock on the output without imposing any restriction on the impact of monetary policy on output.[6] In our framework, we use a 5-variable VAR model: tradable or non-tradable employment; building permit; share of non-performing loans as a percentage of total loans; income; and house price. We assume that a positive shock to house price does not decrease building permits and income and does not increase share of non-performing loans for the next 12 months. We do not impose any restriction on the impact of house price on employment. In other words, we are agnostic about the impact of house price on employment.

3.3 Model

3.3.1 The SVAR Model

In this sub-section we briefly explain the structural VAR model that is used to examine the research question in this paper. A simple structural VAR can be written as:

$$\beta_0 Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_k Y_{t-k} + \epsilon_t, t = 1, 2, ..., T \tag{3.1}$$

where Y_t is an $m \times 1$ vector of logarithm of real house price, tradable/non-tradable employment, housing building permit, real personal disposable income, and ratio of nonperforming loans to total loans. ϵ_t are shocks with no serial correlation, mean zero, and variance-covariance Ω. A conventional VAR model is the reduced form of structural VAR, which can be written as:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_k Y_{t-k} + e_t, t = 1, 2, ..., T \tag{3.2}$$

[6] Some researchers such as Peersman (2005) and Dungey and Fry (2009) consider the effect of multiple shocks in their models, but Uhlig (2005) considers only one shock.

B_k is $\beta_0^{-1}\beta_k$ and e_t is a vector of errors with mean zero, variance-covariance Σ , and no serial correlation. e_t is $\beta_0^{-1}\epsilon_t$, then we have

$$\Sigma = E(e_t e_{t-1}) = \beta_0^{-1}\Omega\beta_0^{-1} \tag{3.3}$$

which gives us variance-covariance matrix of the structural innovations. The solution to the reduced form of SVAR is

$$Y_t = C(L)e_t, \tag{3.4}$$

with $C(L) = (I - B(L))^{-1}$, where $C(L)$ shows the impulse response to a unit innovation in e_t. The fundamental problem in estimating the structural VAR model is that we cannot directly estimate this equation without further identifying restrictions.

Two methods have been proposed for identification of the SVAR in the literature. First, there is formal identification which refers to using certain information about the arrival shock. The second approach is informal identification, which refers to imposing prior restrictions that come from the existing literature and then testing if these satisfy economic theory (Uhlig, 2005).

3.3.2 Sign Restriction SVAR

Whether the identification is formal or informal, there are multiple approaches to identify the structural parameters (shocks) from the reduced form of the SVAR model. In general, we can divide them into two methods: parametric and non-parametric identification. Fry and Pagan (2011) classify identification by the short-run restrictions, the long-run restrictions, and a recursive casual structure as parametric and the sign restriction as a non-parametric. The sign restrictions are more often used in recent literature, because it uses a prior theorizing explicit restrictions while these restrictions are often used implicitly. It also imposes the sign restriction on the impulse responses for few periods after the shock instead of using a specific shape of the impulse responses.Uhlig (2005), Faust (1998), Canova and De Nicolo (2002) and Uhlig (2005) uses priori sign restriction to solve the structural identification problem when they consider the effects of monetary policy shocks.

To choose the fitted impulse responses from the shocks, Uhlig (2005) introduces two approaches, the pure sign restriction and the penalty function by imposing signs for a few periods after shock.

Suppose we have the reduced form VAR model:

$$Y_t = C(L)e_t, \tag{3.5}$$

where Y_t is the m dimensional vector of log real house price, log employment tradable or non-tradable, log house permit, log personal income, and ratio of nonperforming loans to total loans. $C(L)$ is a finite-order autoregressive lag polynomial and e_t is innovations with variance-covariance Σ , and no serial correlation. To get structural shocks, we need to estimate β_0^{-1} since $e_t = \beta_0^{-1}\epsilon_t$. From the reduced VAR model, we have estimated shocks $\hat{e}_t$. To construct a matrix $m \times m$ of β_0^{-1} , we can use some weights that will produce impulse responses with correct signs which reflect that the constructed shocks are uncorrelated, so we design an algorithm to generate weights.

Suppose that there are a total of m fundamental innovations, which are mutually independent and normalized to be of variance 1. They can ,therefore, be written as a vector η of size $m \times 1$ with $E(\eta\eta')$.[7] Now we can write it again as: $A^{-1}\epsilon = \eta$. Where $\Sigma = E[\eta_t'\eta_t] = A^{-1}E[\epsilon_t\epsilon_t']A'^{-1} = A^{-1}A'^{-1}$. To get A^{-1}, let $TT' = \Sigma$ be the Cholesky decomposition of Σ. Then $A^{-1} = TQ$ also satisfy $\Sigma = A^{-1}A'^{-1}$ [8] for any orthogonal matrix $Q(QQ' = I)$.

There are two popular ways to distinguish Q. Given Rotation and Householder transformations(QR decomposition) are two ways to get Q. In this paper, we use the Given Rotation approach as proposed by Uhlig (2005). Since we are interested in studying the impulse responses of employment to house price shock (structural shocks), then we just identify this shock and ignore shocks of other variables.[9]

After determining Q matrix for the identification strategy, we need to get the impulse

[7] Independence of the fundamental innovations is an appealing assumption adopted in much of the VAR literature

[8] $TT' = \Sigma = A^{-1}A'^{-1}$

[9] For more information see Fry and Pagan (2011).

vector. Uhlig (2005) defined that "a" is an impulse vector iff there is an m dimensional vector α of unit length so that $a = Q\alpha$. Given an impulse vector a, we can calculate the impulse response. Following Uhlig (2005), we use the Bayesian approach (a uniform distribution) to get "a". The estimated impulse vector should be multiplied by the orthogonal matrix A and verified to determine whether it is satisfying the impose signs or not. In general, if all these impulse responses satisfy the sign restriction, it is kept; otherwise, it is discarded. In order to test this Uhlig (2005) introduces two different algorithms: the Pure (rejection) Sign Restriction and the Penalty Function approach.

In the case of the rejection approach, the algorithm consists of a number of sub-draws to generate "a" for each posterior draw. The algorithm then checks whether the imposed sign restrictions are satisfied for each restricted response and each restricted period, starting off with response of the shocked variable itself.

In the penalty function approach, the algorithm is not based on the acceptance and rejection of sub-draws. Rather it uses an impulse vector "a" which comes as close as possible to satisfying the imposed sign restrictions by minimizing a function that penalizes sign restriction violations.[10]

We apply the procedure of sign restriction as follows. First, based on Normal-Inverted Wishart prior for B and Σ, we estimate the Normal-Wishart posterior for B and Σ. Second, we use the Cholesky decomposition to extract the orthogonal matrix from Σ.[11] Third, by using uniform distribution we estimate the impulse vector "a". Fourth, take a joint draw from both the unrestricted Normal-Wishart posterior of the VAR parameters and a uniform distribution posterior of "a". Fifth, we multiply the impulse vector times the impulse response from previous step. Sixth, we use the penalty function to choose the best impulse responses which satisfy the sign restriction. Seventh, repeat Steps 2-6.

[10] See Uhlig (2005)for more detail.

[11] The Cholesky decomposition here is just a way to orthogonalise shocks rather than an identification strategy.

3.4 Data

In order to examine the effect of house price on employment, we use monthly data for employment from 2-digit industries, real personal disposable income, new housing building permit, ratio of nonperforming loans to total loans for banks, and real house price index by state level for the period 2001 to 2015.[12]

Employment The Quarterly Census of Employment and Wages Program (QCEW) releases employment and wage information about workers.[13] Data is available by state level and for the two-digit NAICS[14] industries. We consider total employment in the private sector for all 19 two-digit industries.

In order to classify an industry as tradable and non-tradable,we follow Mian and Sufi (2014) and define tradable industries as industries that respond to the national demand while non-tradable industries respond to the local demand.[15] In this paper, we categorize all industries as tradable or nontradable according to their response to the national or local demand as a baseline. We also consider other definitions for robustness check of our results. Figure 2.1 shows non-tradable, tradable and total employment data for all the states. Table 2.1 reports all classifications that we use in this paper.

Real House Price We use state-level house price data from the Freddie Mac. This index reflects the refinancing decisions to measure of price based on loans purchased by Fannie Mae or Freddie Mac. We deflate the nominal house prices by PCE price index to obtain real house prices for each state. Figure 2.1 also shows the house price data for different states in our sample.[16].

Income The Bureau of Economic Analysis releases personal income (thousand of

[12]We consider 45 states because data for other states are not available.

[13]U.S. Census Bureau publishes the County Business Patterns data set

[14]The North American Industry Classification System or NAICS.

[15] Mian and Sufi (2014) use two different methods to classify industries. Based on method one "retail and world trade" classification, they define four categories, tradable, nontradable, construction, and other. One industry is tradable if total exports plus imports are greater than $500M. Non-tradable industries are the retail sector and restaurants. Construction industries include construction, real estate, and land development. The rest of the industries are other. The second method, "Geographical Concentration Based" classification, is based on geographical concentration. Mian and Sufi (2014) explain production of tradable good should be more concentrated geographically while nontradable industries should be geographically dispersed.

[16]See http://www.freddiemac.com for more information

dollars) quarterly for states. We get real personal disposable income by deflating it with the PCE price index. We use the linear interpolation method to get monthly data from the quarterly data.

Housing Building Permit The building permit as a proxy for residential investment has an important role in economic activity. Leamer (2007), Ghent and Owyang (2010) and Strauss (2013) consider the relationship between the housing permits and employment. Strauss (2013) explains that increase in permits can show the expectation of households for future job also they can use their house as collateral to increase consumption. In this paper we use new private housing units authorized by building permits data for each state to control the effect of it which are released by US. Bureau of the Census.

Ratio of Nonperforming Loans to Total Loans The empirical literature suggests that changes in house prices lead to a change in the share of nonperforming loans in balance sheet of banks. Based on this idea, we use share of nonperforming loans in total loans for each state in our paper. We get monthly data for each state from the Federal Financial Institutions Examination Council(US).[17]

3.5 Empirical Results

3.5.1 Cyclical Correlation Between House Prices and Employment

We first undertake a preliminary exercise in examining the relationship between two types of employment and house prices. For this purpose, we decompose the movements in tradable and non-tradable employment and real house prices for all 45 states in our sample into a trend and a cycle using the Hodrick-Prescott (HP) filter. Table 2.2 reports the correlation between the cycle of the housing price and the cycle of both the tradable and non-tradable employment. Our results clearly show that there is a strong positive correlation between the non-tradable employment cycle and the cycle of housing prices for all the states. These results are consistent with Mian and Sufi (2014) who find significant correlation between non-tradable employment losses and the housing net worth decline.

[17] www.federalreserve.gov/apps/mdrm/data-dictionary.

We also find positive correlation between the tradable employment cycle with the cycle of house prices in all the states except Nebraska and Massachusetts. The average of the correlation of the non-tradable employment cycle with the house price cycle is 0.52. There is significant heterogeneity in the correlation with the lowest correlation of 0.07 for Massachusetts and the highest correlation of 0.92 for Florida. The average of the correlation across states between the tradable employment cycle and the cycle of housing prices is 0.39. The results for the correlation between the HP cycle of tradable and non-tradable employment with the HP cycle of house prices clearly suggest that non-tradable employment for most the states have higher correlation with house prices.

3.5.2 Estimating Employment Response to House Price Shock from Agnostic Identification

The correlation analysis suggests that there is a strong positive relationship between house prices and employment with the correlation between non-tradable employment cycle and house price cycle substantially higher than the correlation between tradable employment cycle and house price cycle for most of the states. Even though the results from correlation analysis is informative, it does not provide us a detailed answer on the relationship between employment and house prices. For example, how does tradable or non-tradable employment react to a shock to house price? How persistent are the responses to the house price shocks? How significant are the heterogeneities in the responses across different states? How much variation at different forecast horizons in tradable and non-tradable employment can be explained by house price shocks?

To examine these questions in detail, we use a structural VAR with agnostic identification as proposed by Uhlig (2005). In the first step of estimation, we calculate the number of the lags for the VAR system without constant and a time trend [18] that includes the level of the logs of the real housing prices, real personal disposable income, and new private housing units authorized by building permits and ratio of nonperforming loans to total loans. We adopt the Markov Chain Monte Carlo algorithm for the estimation

[18]See Uhlig (2005) and Uhlig (1994) for more information

of this model with sign restrictions. Following Uhlig (2005), we use Bayesian approach to estimate the VAR parameters given the assumed Normal-Wishart prior starting in the first step. We use 40000 draws from posterior and 20000 sub-draws for each of them to generate impulse responses for 60 step-ahead (5 years). For testing robustness of the results related to the number of acceptable draws, we also run it 2000 times (Uhlig, 2005).

We identify the effect of the house price shock by directly imposing the sign restrictions on the impulse responses of other variables. For identification, we assume that following a positive shock to the house price, building permits and state-level income do not decrease for 12 months, while the share of nonperforming loans in total loans also do not increase for 12 months. We leave the response of tradable and non-tradable employment unrestricted. We are therefore agnostic about the response of different types of employment to house price shocks. Table 2.5 reports the details of the nature of the sign restrictions being imposed in the model. As compared to other methods of identification, these restrictions are very mild. These restrictions do help us in the identification of the responses of the house price shock on employment over time.

Figure 2.3 shows the impulse responses of non-trabable employment to one standard deviation shock to house prices. The estimates for the median, 16 and 84 quantiles are reported. The main result of the graph can be interpreted as follows:

1. We find that both the tradable and non-tradable employment react strongly and positively to house price shock and there is significant heterogeneity in the persistence of the response across different states.

2. The response of non-tradable employment is higher on average than the response of tradable employment.

3. Ratio of nonperforming loans to total loans for all of states reacts negatively and slowly to a house price shock. It takes typically 2 years for the shock to disappear.

4. Building permits react positively and drop after around one year.

5. Income reacts slightly positively at the beginning and then starts to increase and reaches a pleateau.

6. House prices revert to mean very slowly in response to its own shock implying high degree of persistence in house prices across different states.

Our results show that Nevada has the highest average response of non-tradable employment to one standard deviation house price shocks, while New Jersey has the lowest average response . Figure 2.4 shows the results for the response of tradable employment to house price shocks. Nevada also has the highest average response of tradable employment, whereas Maryland has the lowest response. The positive response of NT and T is consistent with the literature view. Our finding clearly show if there is a positive shock from the house price then employment of NT and T industries increase while Mian and Sufi (2014) show the decline in housing net worth decrease NT and they do not find significant results for T.

To compare the differential impact of employment to house prices shock, Figure 2.5 presents the median impulse responses of tradable and non-tradable employment to one standard deviation house price shock from the SVAR model with sign restrictions. Table 2.3 also shows that the average of the medium impulse responses of non-tradable employment to a house price shock is higher than it is for tradable employment to the same housing price shock for 28 states.[19] Our results for these 28 states are consistent with Mian and Sufi (2014) findings who find that counties with significant decline in house prices were also the counties that witnessed significant decline in jobs during the financial crisis. While our results are broadly consistent with their resutls, there are some states where the tradable employment respond more to house price shocks than non-tradable employment. The argument that non-tradable employment is more sensitive to local housing market is also supported by our results. Moreover, we find that tradable employment also responds positively to local house price shocks. This result is different than what Mian and Sufi (2014) find in their study. This is not surprising as their study looked at short-term

[19] these states are Alabama, Arizona, Arkansas, California, Connecticut, Florida, Georgia, Idaho, Illinois, Kentucky, Louisiana, Maryland, Massachusetts, Minnesota, Mississippi, Montana, Nebraska, Nevada, North Carolina, North Dakota, Ohio, Pennsylvania, South Carolina, Tennessee, Texas, Virginia, Washington, Wisconsin

response of employment to housing bust. In our analysis, we are estimating the dynamic response and a positive/negative wealth effect arising out of an increase/decrease in house price will also have an impact on tradable employment, albeit the impact on tradable employment may be different than the impact on non-tradable employment.

Looking at the nature of the dynamic response, we find that both the tradable and non-tradable employment follow a hump-shaped pattern in most of the states. The median response for most of the states plateau around 20-30 months. As explained earlier, we also find significant heterogeneity both in the magnitude as well as the speed at which the plateau is reached for the different states. The persistent effect of house price shock on employment may also provide an explanation on the puzzle of jobless recovery that immediately followed the financial crisis of 2008-09. Our results show that it takes almost 3-4 years for the impact of house price shock on employment to disappear.

3.5.3 Variance Decomposition

We can also use the estimated SVAR model with sign restrictions to estimate the percentage of variations in different variables in the VAR system arising due to house price shocks at different forecast horizons. Table 2.6, 2.7, and 2.8 report the results for this variance decomposition exercise for both the tradable and the non-tradable SVAR model. The results in a sense reinforces the results discussed above for the impulse responses We find that for the states where non-tradable employment responds more to house price shocks are also the states where house price shocks explain a bigger percentage of forecast error variance especially at short horizons. One of the interesting findings of the variance decomposition exercise is that at long horizons , around 20-30 percent of the variation in employment can be explained by house price shocks implying relatively large role of the housing market in the job market in different states. As expected, we also find substantial heterogeneity in the percentage variation of employment explained by house price shocks for different states. Even at very short-horizons (1- and 2-months ahead), we find that for states like Arizona, California, Florida, Nevada, New Mexico, New York, South Carolina, Texas and Virginia, almost 20-30 percent variation in non-tradable employment can be explained by house price shocks.

3.5.4 Differential Effect Channel

The results presented above suggest that non-tradable employment on average responds more to house price shocks than tradable employment. In this sub-section, we dig deeper into the causes for this differential effect. In particular, we examine the relationship between the differential impact and the correlation of house prices with consumption and also examine whether states with higher volatility in house prices are also the states with bigger response of employment to house price shocks.

One of the reasons proposed for the differential effect of house price shock on employment is that demand channel is stronger for non-tradable employment. This is based on the idea that states where consumption is more sensitive to house prices are also the states where demand channel will be stronger. Using state level personal consumption expenditure data, we examine this hypothesis. In the first step, we calculate the correlation between the cycle of the real house prices and the cycle of consumption. Then we examine whether the states with high correlation between the cycles of consumption and house prices are also the states where non-tradable employment responds higher on average. Table 2.4 reports the results for this exercise. Not surprisingly, we find that the states with higher correlation between the cycles of house price and consumption also have higher response of non-tradable employment on average. The average of this correlation is 0.26 for non-tradable employment, whereas the average of this correlation is only 0.09 for the tradable employment

We also want to explore whether differences in the housing market volatility across states plays any role in this differential effect. To examine the effect of volatility on the relative response of two types of employment, we run a regression from the average impulse responses of tradable and non-tradable employment on the deviation of the house prices growth for each state. Our results show the standard deviation of real house price growth can explain 39% of the variations in the average of the impulse responses for non-tradable employment whereas it is 15% for tradable employment. These results are consistent with Mian and Sufi (2014) who also find similar results. The

3.5.5 Robustness Check

To examine if our results from the baseline model are robust, we present three types of the robustness checks. First, we check for the robustness of the identification of structural shocks. As we explained in the previous section, there are many values for the impulse vector ("a") that satisfy the sign restriction. Fry and Pagan (2011)suggest median target(MT) approach to selecting a single value for the impulse vector "a" . In this method, we choose a value for "a" that produces impulse responses that are enough close to the median responses. To choose the best draw for "a" we performed 1000 iteration (Fry and Pagan, 2011). The differences between the MT impulse responses and the median responses from the penalty function method show how results from the penalty function are biased.

Figure 3.6 shows our results from the MT approach. As we can see, the gap between the penalty function and the MT approach is negligible. These results suggest that identification for "a" based on the penalty function is robust to the alternative method of imposing sign restriction.

The second robustness check is done on the size of the VAR system. To see whether our results are sensitive to the set of variables used in the VAR system, we drop income from our 5-variable baseline model. Again the sign restriction remains the same as the baseline model where we assume that a positive shock to house price does not decrease building permits and does not increase non-performing loans for the next 12 months. Figure 3.7.1 in the appendix shows the impulse responses for this exercise. The results clearly show that our baseline results are not sensitive to the inclusion of income in the VAR system.

In addition, we have also considered a robustness check where the sign restrictions are imposed for 6 months in place of the baseline restriction of 12 months. That is, we assume that a positive shock to house price does not lead to a decline in building permit and income and does not lead to an increase in nonperforming loan for next 6 months. The results obtained from this exercise (not reported) also show that our results are robust to this restriction.

3.6 Conclusion

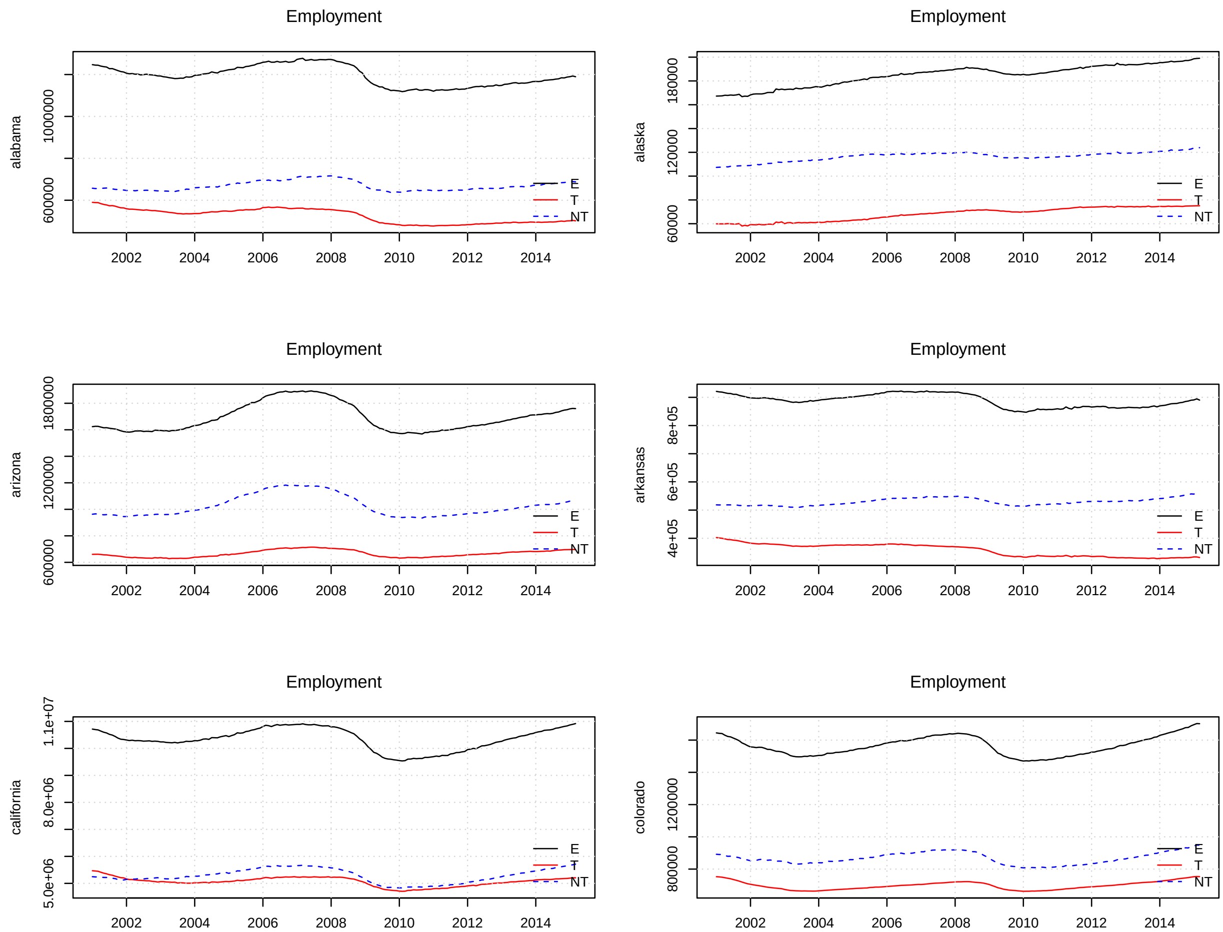
This paper examines the effect of house prices on employment by using time-series data on 45 U.S. states over the sample period 2001-2014. We also examine whether there is a differential impact of house prices on non-tradable employment as compared to the tradable employment. To do so, we use a multivariate structural VAR model with sign restrictions. We assume that a positive shock to house price does not lead to a decline in income and builiding permits and an increase in non-performing loans for 12 months. We keep the response of employment to house price shock unrestricted. Our results show significant response of employment to house price shock with a hump-shaped response for most of the states. In particular, we find that in 28 out of 45 states, the response of non-tradable employment is higher than tradable employment. There is significant heterogeneity, however, in the magnitude of responses. On average we find that states with higher volatility in house prices have higher response of non-tradable employment to house price shocks. We also find that states with higher correlation between consumption cycle and house price cycles are also the states with relatively higher response of non-tradable employment as compared to the tradable employment.

Table 3.1: Industries Classification

	Baseline		case 1		Case 2		Case 3	
All Industries	T	NT	T	NT	T	NT	T	NT
11-Agriculture,forestry,fishing	✓		✓		✓		✓	
21-mining,quarrying and oil and gas	✓		✓		✓		✓	
22-Utilities		✓				✓		
23-Construction		✓						
31-33-manufacturing	✓		✓		✓		✓	
42-Wholesale trade	✓							
44-45- retail trade		✓		✓		✓		✓
48-49- Transportation and warehousing		✓				✓		
51-information	✓		✓					
52-finance and insurance	✓		✓					
53-real state-rental and leasing		✓						
54-professional and technical services	✓							
56-Administrative and waste services		✓				✓		
61-Education services	✓			✓				
71-Art,Entertainment recreation	✓			✓				
72-Accommodation and food services		✓		✓		✓		✓

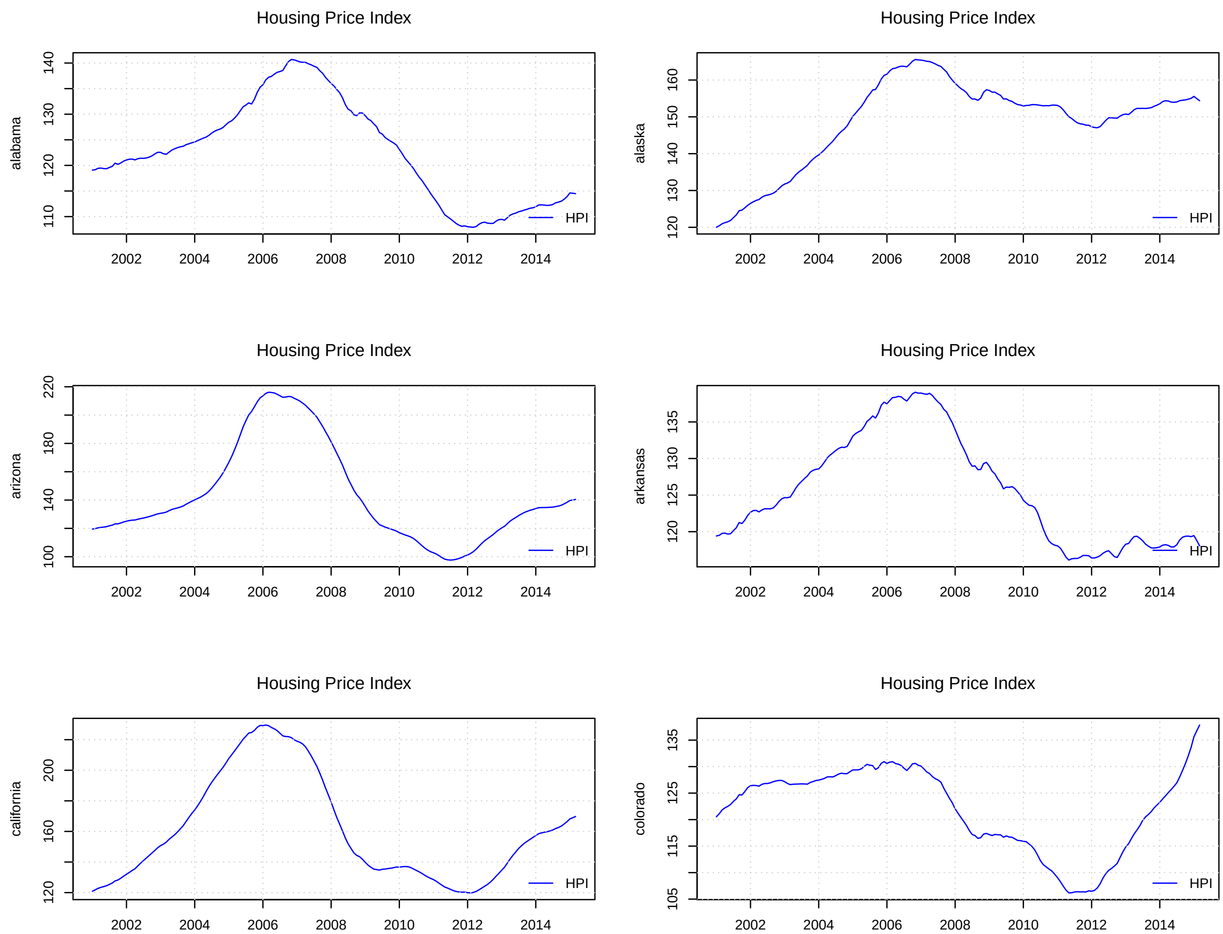
Note: The table reports all industries, tradable (T) and non-tradable (NT) industries based on different classification.

Figure 3.1: Employment



Notes: This graph presents the employment for Non-Tradable and Tradable industries and total employment from 2001 to 2014.The graph for the rest of states are not reported to conserve space but available upon request.

Figure 3.2: Housing Prices



Notes: This graph presents the real house prices from 2001 to 2014. The graph for the rest of states are not reported to conserve space but available upon request.

Table 3.2: Correlation Between Employment Cycle and House Price Cycle

	Tradable	Non-Trabable
Alabama	0.6611	0.6226
Alaska	0.1418	**0.4621**
Arizona	0.8338	**0.9054**
Arkansas	0.4976	**0.5969**
California	0.4456	**0.6740**
Colorado	0.2335	**0.4202**
Connecticut	0.1361	**0.4172**
Florida	0.7786	**0.9243**
Georgia	0.6045	**0.6851**
Idaho	0.8176	**0.8743**
Illinois	0.4099	**0.5486**
Indiana	0.2808	**0.2831**
Kansas	0.1647	**0.1977**
Kentucky	0.2830	**0.3316**
Louisiana	0.1866	**0.2534**
Iowa	0.1224	**0.3252**
Maryland	0.6038	**0.7047**
Massachusetts	-0.3332	**0.0796**
Michigan	0.5967	**0.6402**
Minnesota	0.2486	**0.4530**
Mississippi	0.6412	0.6222
Missouri	0.3668	**0.4628**
Montana	0.6986	**0.7129**
Nebraska	-0.0576	**0.2028**
Nevada	0.7824	**0.8656**
New Hampshire	0.0617	**0.4357**
New Jersey	0.2463	**0.5026**
New Mexico	0.7156	**0.7738**
New York	0.1124	**0.1836**
North Carolina	0.5880	**0.6341**
North Dakota	0.2369	**0.3494**
Ohio	0.1445	**0.2330**
Oklahoma	0.1084	**0.2720**
Oregon	0.7070	**0.8051**
Pennsylvania	0.1772	**0.3695**
South Carolina	0.5730	**0.6607**
South Dakota	0.3224	0.2975
Tennessee	0.6288	0.6055
Texas	0.3440	**0.4631**
Utah	0.8302	**0.8615**
Vermont	0.3199	**0.5958**
Virginia	0.4731	**0.6658**
Washington	0.5575	**0.8254**
West Virginia	0.3509	**0.4272**
Wisconsin	0.1683	**0.4158**

Note: This table presents the correlation between the cycle of Non-tradable employment and house prices also the correlation between tradable employment and house prices. To get the cycles , we use Hodrick Prescott filter.

Table 3.3: The Average Median Impulse Responses

	Non-Tradable	Tradable
Alabama	**0.00591**	0.0058
Alaska	0.0028	0.0033
Arizona	**0.0088**	0.0058
Arkansas	**0.0035**	0.0035
California	**0.0066**	0.0048
Colorado	0.0073	0.0073
Connecticut	**0.0074**	0.0055
Florida	**0.0080**	0.0050
Georgia	**0.0081**	0.0068
Idaho	**0.0076**	0.0057
Illinois	**0.0050**	0.0046
Indiana	0.0043	0.0055
Kansas	0.0060	0.0084
Kentucky	**0.0053**	0.0052
Louisiana	**0.0042**	0.0036
Iowa	0.0028	0.0034
Maryland	**0.0031**	0.0022
Massachusetts	**0.0049**	0.0043
Michigan	0.0031	0.0047
Minnesota	**0.0054**	0.0048
Mississippi	**0.0060**	0.0041
Missouri	0.0049	0.0050
Montana	**0.0070**	0.0052
Nebraska	**0.0054**	0.0032
Nevada	**0.0126**	0.0109
New Hampshire	0.0027	0.0030
New Jersey	0.0021	0.0030
New Mexico	0.0046	0.0054
New York	0.0034	0.0059
North Carolina	**0.0077**	0.0063
North Dakota	**0.0040**	0.0032
Ohio	**0.0057**	0.0049
Oklahoma	0.0071	0.0075
Oregon	0.0038	0.0041
Pennsylvania	**0.0036**	0.0030
South Carolina	**0.0082**	0.0056
South Dakota	0.0036	0.0078
Tennessee	**0.0035**	0.0034
Texas	**0.0069**	0.0063
Utah	0.0022	0.0047
Vermont	0.0056	0.0058
Virginia	**0.0046**	0.0037
Washington	**0.0080**	0.0058
West Virginia	0.0033	0.0038
Wisconsin	**0.0048**	0.0040

Note: This table present the average median impulse responses of tradable and non-tradable to a positive house price shock.

Table 3.4: House Price-Consumption Correlation and Employment

Consumption	corr(NT,corr1)	corr(T,corr1)
Personal consumption expenditures	**0.3259**	0.0950
Goods	**0.3253**	0.0807
Durable goods	**0.3028**	0.0325
Motor vehicles and parts	**0.2887**	0.1357
Furnishings and durable household equipment	**0.3584**	0.0257
Recreational goods and vehicles	**0.3036**	0.0475
Other durable goods	**0.1345**	-0.0651
Nondurable goods	**0.3057**	0.0942
Food and beverages purchased for off-premises consumption	**0.3504**	0.1655
Clothing and footwear	**0.1410**	-0.1348
Gasoline and other energy goods	**0.1800**	-0.0738
Other nondurable goods	**0.4511**	0.3340
Services	**0.2947**	0.1753
Household consumption expenditures (for services)	**0.3484**	0.1862
Transportation services	**0.3228**	0.0636
Recreation services	0.1224	0.1292
Food services and accommodations	**0.3360**	0.1934
Financial services and insurance	**0.2969**	0.0142
Other services	0.0392	0.1200
Less: Receipts from sales of goods and services by nonprofit institutions	0.1634	0.2375

Note: This table provide the correlation between the average median impulse responses for Non-tradable (or Tradable) and the correlation between the cycle of consumption expenditure and the cycle of house prices.

Table 3.5: Sign Restriction

Variable shock	HPI	NPLT	I	PB	E
HPI	> 0	< 0	> 0	> 0	> 0 or < 0

Table 3.6: Variance Decomposition

State	Period	T	NT	State	Period	T	NT
Alabama	1	6.67	12.42	Georgia	1	1.21	2.23
	2	7.65	13.21		2	2.89	3.16
	5	14.05	18.49		5	7.49	7.38
	10	19.98	21.04		10	15.73	14.88
	20	21.6	19.92		20	27.12	26.65
	30	20.95	18.33		30	30.31	30.15
Alaska	1	1.29	17.59	Idaho	1	5.22	14.03
	2	2.44	17.73		2	6.29	14.25
	5	5.3	19.51		5	10.04	15.76
	10	11.1	20.86		10	14.05	18.31
	20	17.51	22.87		20	20.86	22.79
	30	22.92	24.26		30	23.91	24.35
Arizona	1	1.66	23.35	Illinois	1	1.43	3.29
	2	3.16	22.95		2	2.34	4.22
	5	8.63	22.76		5	7.45	10.58
	10	15.8	23.78		10	21.2	25.23
	20	23.19	25.65		20	36.41	38.95
	30	25.03	25.94		30	37.04	39.77
Arkansas	1	13.73	11.66	Indiana	1	4.56	5.23
	2	13.83	12.59		2	5.09	5.64
	5	14.46	13.8		5	6.99	8.19
	10	15.23	15.18		10	11.84	13.58
	20	16.66	17.61		20	19.93	20.25
	30	17.61	18.83		30	21.8	21.9
California	1	6.38	19.82	Kansas	1	3	11.51
	2	6.64	19.8		2	3.83	12.35
	5	8.52	20		5	7.44	16.12
	10	12.52	21.38		10	17.66	24.44
	20	20.98	27.99		20	28.65	29.1
	30	25.93	30.39		30	31.78	29.91
Colorado	1	9.19	5.02	Kentucky	1	19.18	16.7
	2	9.58	5.56		2	18.88	17.11
	5	10.73	6.98		5	19.06	17.97
	10	13.89	10.48		10	19.33	18.96
	20	19.97	19.72		20	20.55	21.76
	30	23.84	22.85		30	20.41	22.06
Connecticut	1	8.73	5.38	Louisiana	1	3.12	0.98
	2	9.07	7.61		2	3.65	1.56
	5	12.01	16.42		5	7.3	3.54
	10	17	24.91		10	11.27	6.26
	20	23.18	31.21		20	15.33	10.91
	30	26.06	32.42		30	18.26	13.3
Florida	1	2.01	26.29	Iowa	1	10.39	3.27
	2	2.95	26.06		2	10.57	5.13
	5	6.63	26.18		5	11.42	9.2
	10	11.73	31.26		10	18.85	17.5
	20	24.42	38.4		20	32.02	32.44
	30	31.39	38.27		30	35.82	34.7

Note:

Table 3.7: Variance Decomposition

State	Period	T	NT	State	Period	T	NT
Maryland	1	8.99	10.21	Nevada	1	38.53	26.68
	2	10.67	11.77		2	37.87	26.17
	5	11.29	12.85		5	37.18	27.28
	10	14.36	15.61		10	36.4	33
	20	19.92	21.61		20	37.77	40.04
	30	24.31	25.26		30	36.11	39.7
Massachusetts	1	1.94	7.15	New Hampshire	1	2.56	7.61
	2	3.61	8.85		2	3.49	8.36
	5	9.87	13.85		5	4.86	9.63
	10	16.42	17.73		10	6.75	14.71
	20	22.93	23.54		20	13.66	20.6
	30	25.54	25.07		30	19.56	23.23
Michigan	1	6.07	5.69	New Jersey	1	1.12	1.66
	2	6.59	6.07		2	2.35	2.29
	5	8.46	7.51		5	7.43	5.87
	10	10.29	9.44		10	11.14	9.86
	20	17.37	19.21		20	16.76	15.59
	30	21.87	24.23		30	19.96	17.95
Minnesota	1	2.66	7.23	New Mexico	1	4.95	20.47
	2	3.01	7.71		2	5.41	20.29
	5	5.79	11.22		5	7.02	20.94
	10	11.46	17.86		10	12.1	21.74
	20	20.22	24.13		20	20.24	21.51
	30	24.34	25.61		30	22.81	20.5
Mississippi	1	11.91	3.97	New York	1	15.8	42.62
	2	12.43	4.42		2	15.81	40.53
	5	12.73	6.07		5	16.63	34.28
	10	13.3	10.92		10	19.96	32.95
	20	16.44	20.71		20	26.07	29.64
	30	18.19	23.75		30	28.76	25.41
Missouri	1	12.64	2.93	North Carolina	1	6.06	15.91
	2	13.12	4.53		2	6.31	17.08
	5	15.21	7.43		5	8.01	19.52
	10	16.91	11.2		10	12.72	22.6
	20	19.05	20.96		20	20.42	27.15
	30	20.18	25.87		30	23.86	27.89
Montana	1	5.42	57.04	North Dakota	1	22.29	7.73
	2	6.01	55.82		2	21.99	8.36
	5	8.57	54.42		5	22.5	12.84
	10	13.24	51.89		10	24.89	20.81
	20	17.66	46.22		20	25.34	24.55
	30	18.71	41.36		30	23.13	24.02
Nebraska	1	1.01	19.81	Ohio	1	2.06	1.11
	2	2.13	19.86		2	2.91	1.95
	5	4.36	19.84		5	8.47	5.57
	10	9.34	21.42		10	20.08	20.02
	20	17.75	24.9		20	30.53	37.41
	30	21.92	26.09		30	31.31	39.47

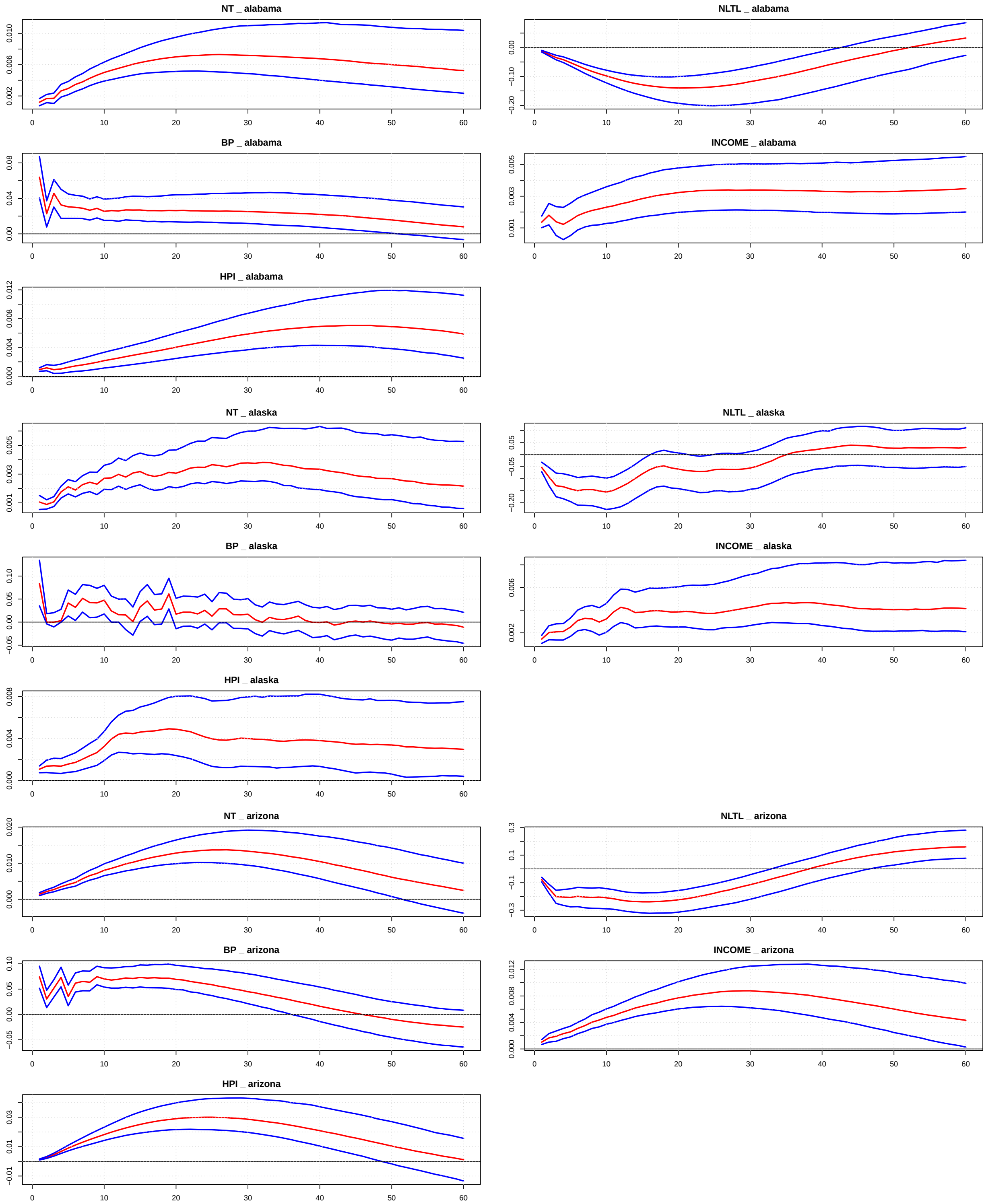
Note:

Table 3.8: Variance Decomposition

State	Period	T	NT	State	Period	T	NT
Oklahoma	1	4.95	4.73	Utah	1	20.48	19.18
	2	5.86	6.32		2	20.61	19.1
	5	8.92	9.52		5	21.01	19.04
	10	14.31	15.13		10	21.67	19.1
	20	24.87	22.84		20	23.71	22.46
	30	28.92	26.66		30	23.42	22.94
Oregon	1	17	11.67	Vermont	1	11.01	6.3
	2	17.09	11.72		2	11.21	7.18
	5	17.16	12.02		5	12.76	12.55
	10	17.65	12.85		10	16.51	17.9
	20	18.45	17.27		20	20	21.51
	30	19.3	20.56		30	21.42	22.72
Pennsylvania	1	1.04	5.23	Virginia	1	19.18	39.79
	2	2.25	6.18		2	19.43	39.33
	5	7.83	11.64		5	20.22	37.43
	10	12.67	17.2		10	22.2	34.35
	20	19.15	24.72		20	25.79	34.05
	30	23	27.86		30	26.54	33.38
South Carolina	1	10.15	19.75	Washington	1	4.62	11.43
	2	11.6	21.06		2	5.7	11.7
	5	14.13	24.3		5	8.9	15.19
	10	18.31	26.56		10	12.25	26.06
	20	27.26	30.36		20	18.66	34.71
	30	30.81	31.43		30	25.85	35.63
South Dakota	1	24.03	21.86	West Virginia	1	13.1	13.57
	2	23.89	21.96		2	13.21	14.31
	5	24.06	21.95		5	13.77	15.29
	10	24.75	22.66		10	15.03	16.78
	20	26.09	23.13		20	16.04	18.67
	30	26.85	23.01		30	17.29	20.49
Tennessee	1	1	1.83	Wisconsin	1	4.63	1.28
	2	2.03	2.74		2	4.96	2.26
	5	8.28	5.99		5	7.31	8.84
	10	18.52	12.64		10	12.85	19.94
	20	29.49	22.65		20	21.31	27.54
	30	32.1	23.13		30	24.11	28.3
Texas	1	38.71	23.81				
	2	38.4	23.97				
	5	37.24	24.96				
	10	34.84	27.04				
	20	32.12	29.21				
	30	30.5	29.37				

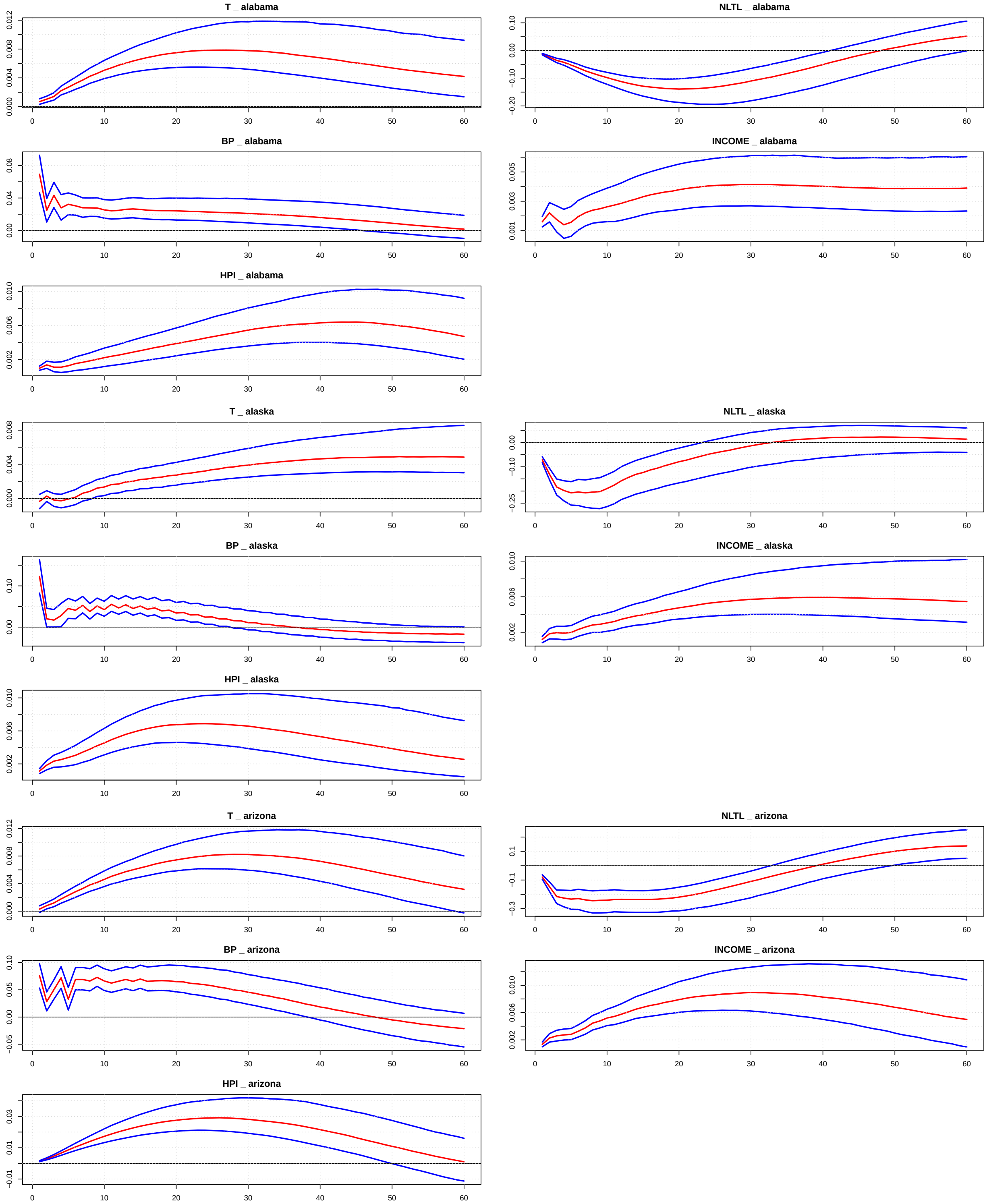
Note:

Figure 3.3: Impulse Responses from The House Price Shock (Baseline Model)



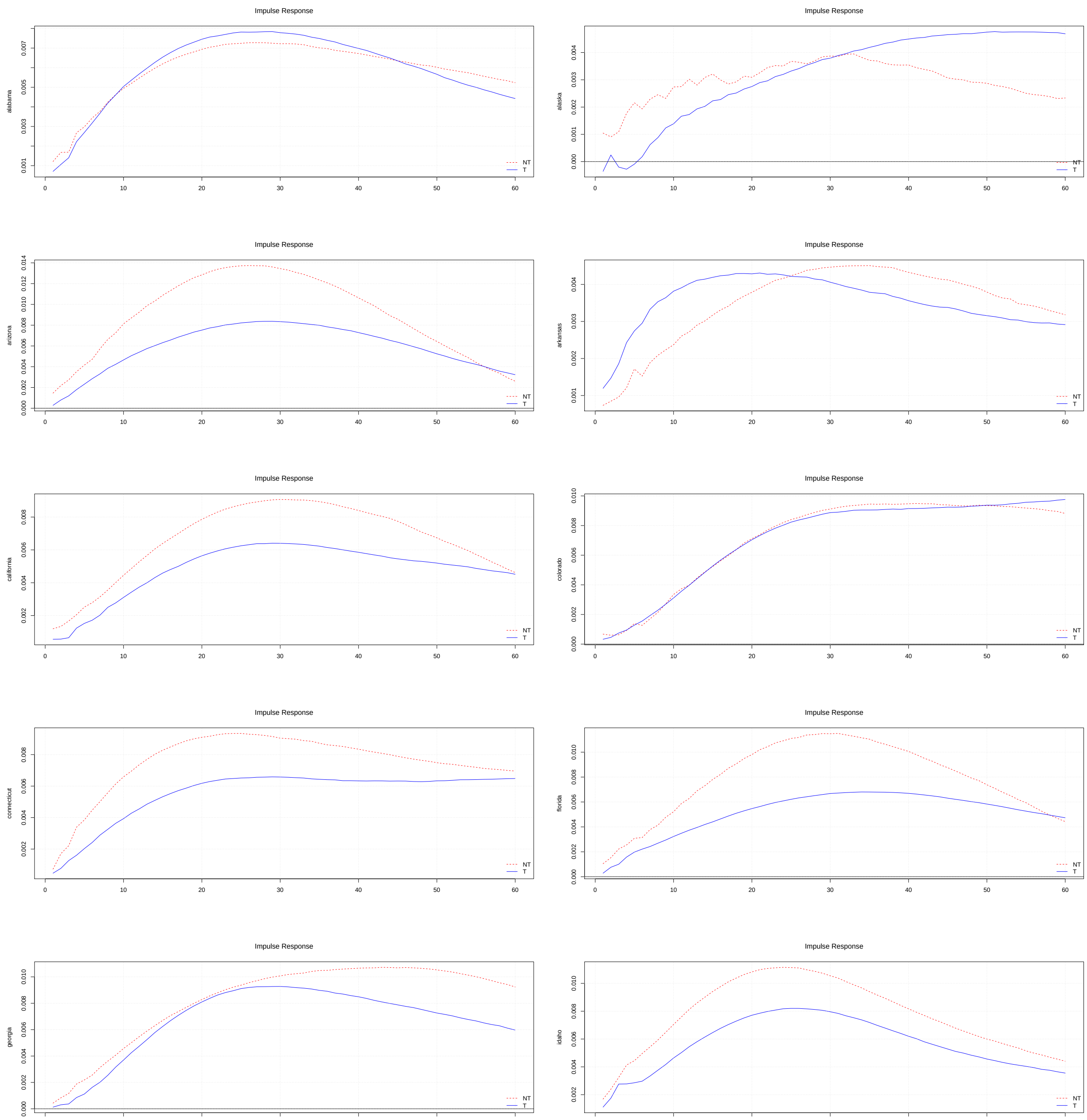
Notes: Impulse responses form a housing price shock on Non-Tradable (NT) employment, using the penalty function approach in the sign restriction method for the baseline model. The results for the rest of states are not reported to conserve space but available upon request.

Figure 3.4: Impulse Responses from The House Price shock (Baseline Model)

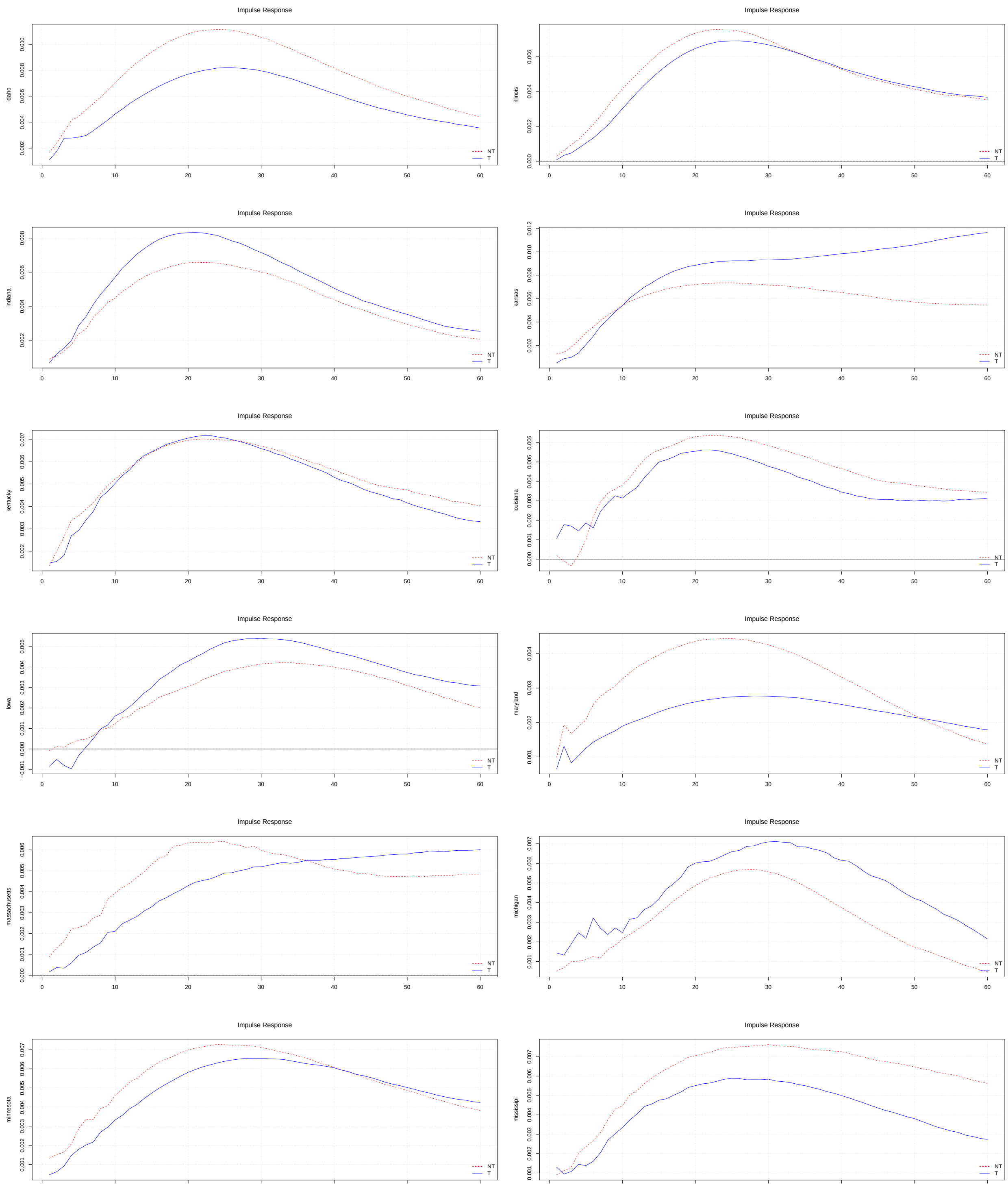


Notes: Impulse responses form a housing price shock on Tradable (T) employment, using the penalty function approach in the sign-restriction method for baseline model. The results for the rest of states are not reported to conserve space but available upon request.

Figure 3.5: Impulse Responses for T and NT



Notes: The graphs show the median impulse responses of Tradable and Non-Tradable to a housing price shock.



Impulse Response
idaho
NT
T
Impulse Response
illinois
NT
T
Impulse Response
indiana
NT
T
Impulse Response
kansas
NT
T
Impulse Response
kentucky
NT
T
Impulse Response
louisiana
NT
T
Impulse Response
iowa
NT
T
Impulse Response
maryland
NT
T
Impulse Response
massachusetts
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michigan
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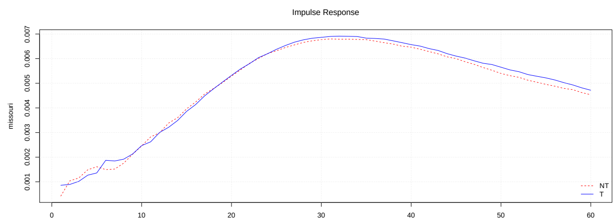
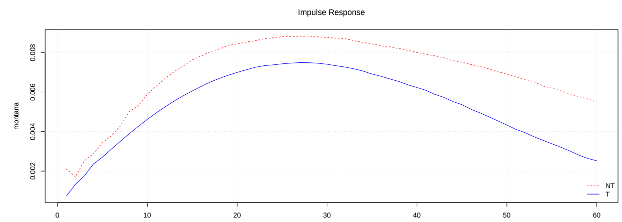
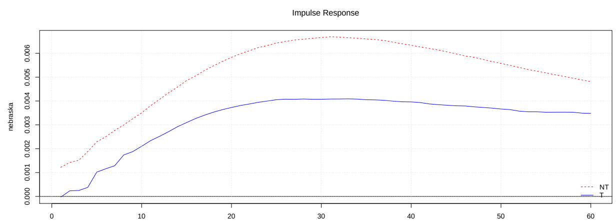
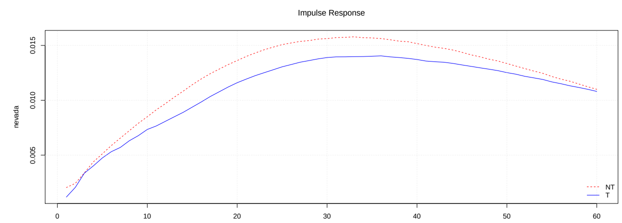
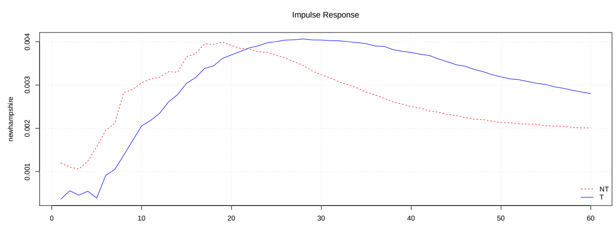
Impulse Response
minnesota
NT
T
Impulse Response
mississippi
NT
T

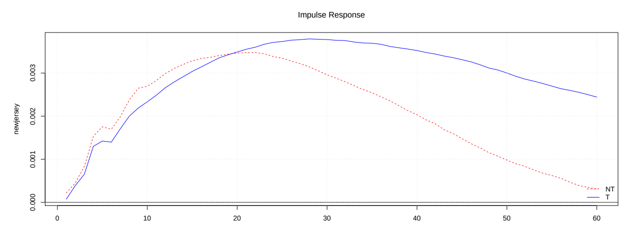

Impulse Response
missouri
NT
T


Impulse Response
montana
NT
T


Impulse Response
nebraska
NT
T


Impulse Response
nevada
NT
T


Impulse Response
newhampshire
NT
T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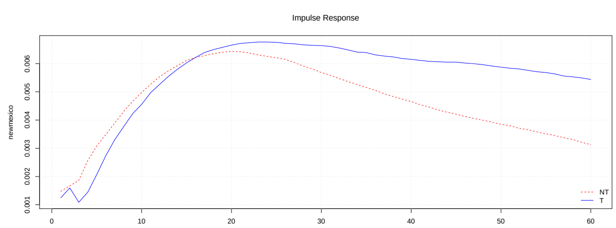
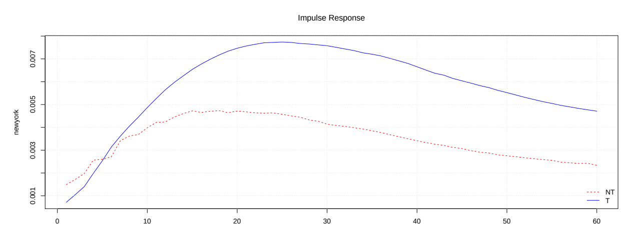
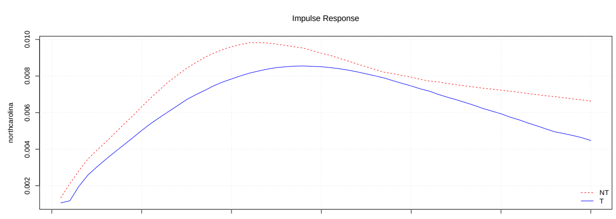
newjersey
NT
T


Impulse Response
newmexico
NT
T


Impulse Response
newyork
NT
T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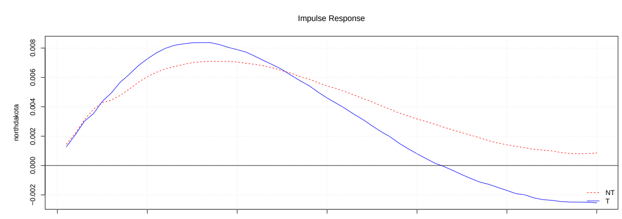
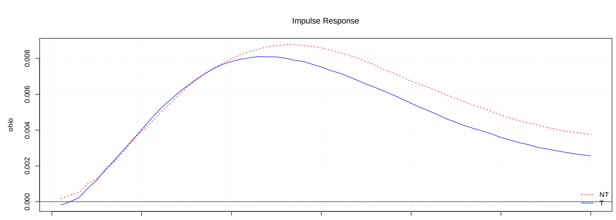
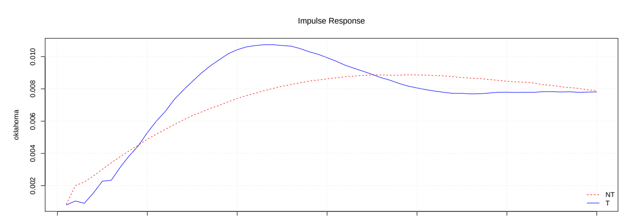
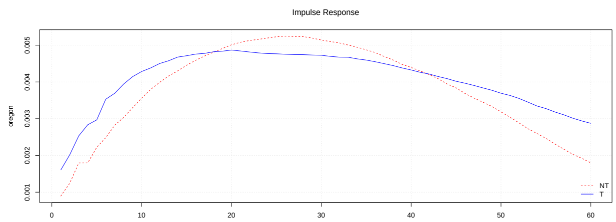
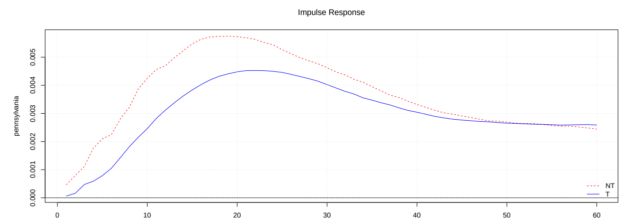
northcarolina
NT
T

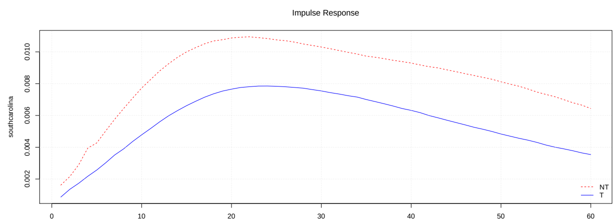

Impulse Response
northdakota
NT
T

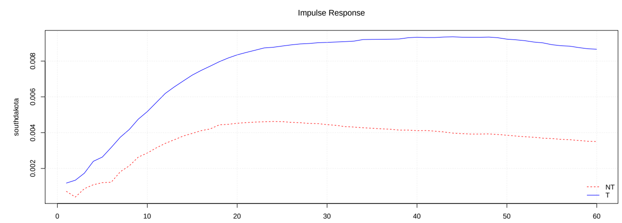

Impulse Response
ohio
NT
T


Impulse Response
oklahoma
NT
T


Impulse Response
oregon
NT
T


Impulse Response
pennsylvania
NT
T


Impulse Response
southcarolina
NT
T


Impulse Response
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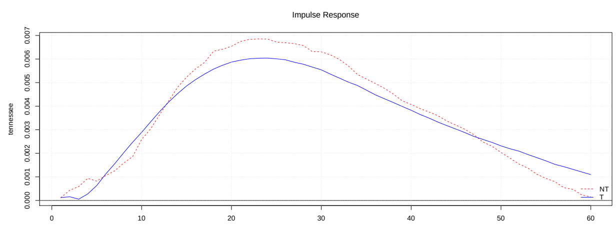
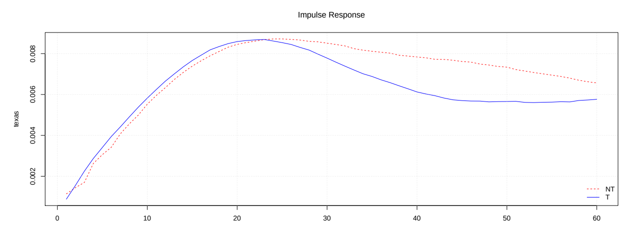
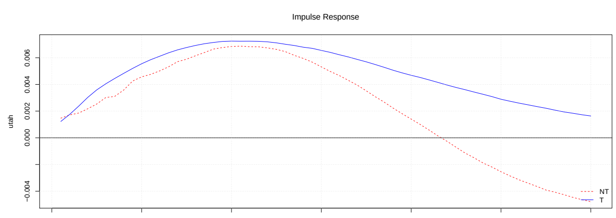
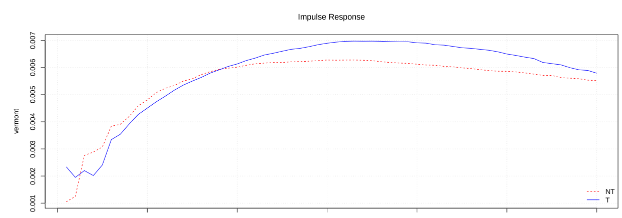
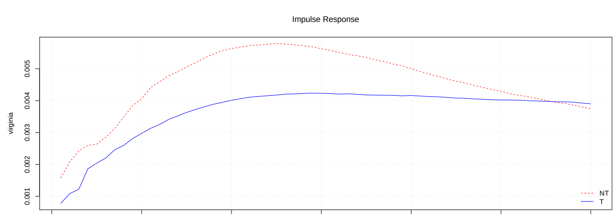
NT
T

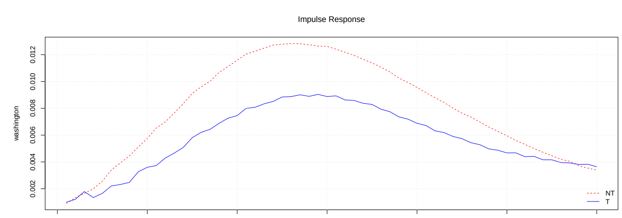

Impulse Response
tennessee
NT
T

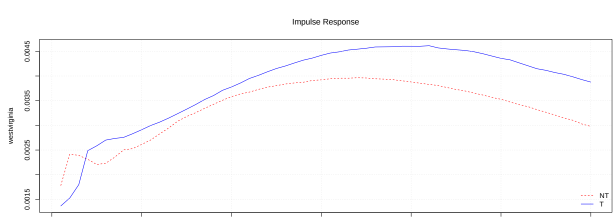

Impulse Response
texas
NT
T


Impulse Response
utah
NT
T


Impulse Response
vermont
NT
T


Impulse Response
virginia
NT
T


Impulse Response
washington
NT
T


Impulse Response
westvirginia
NT
T

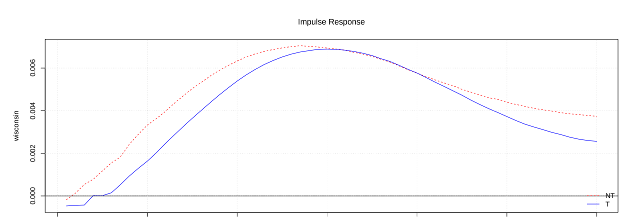
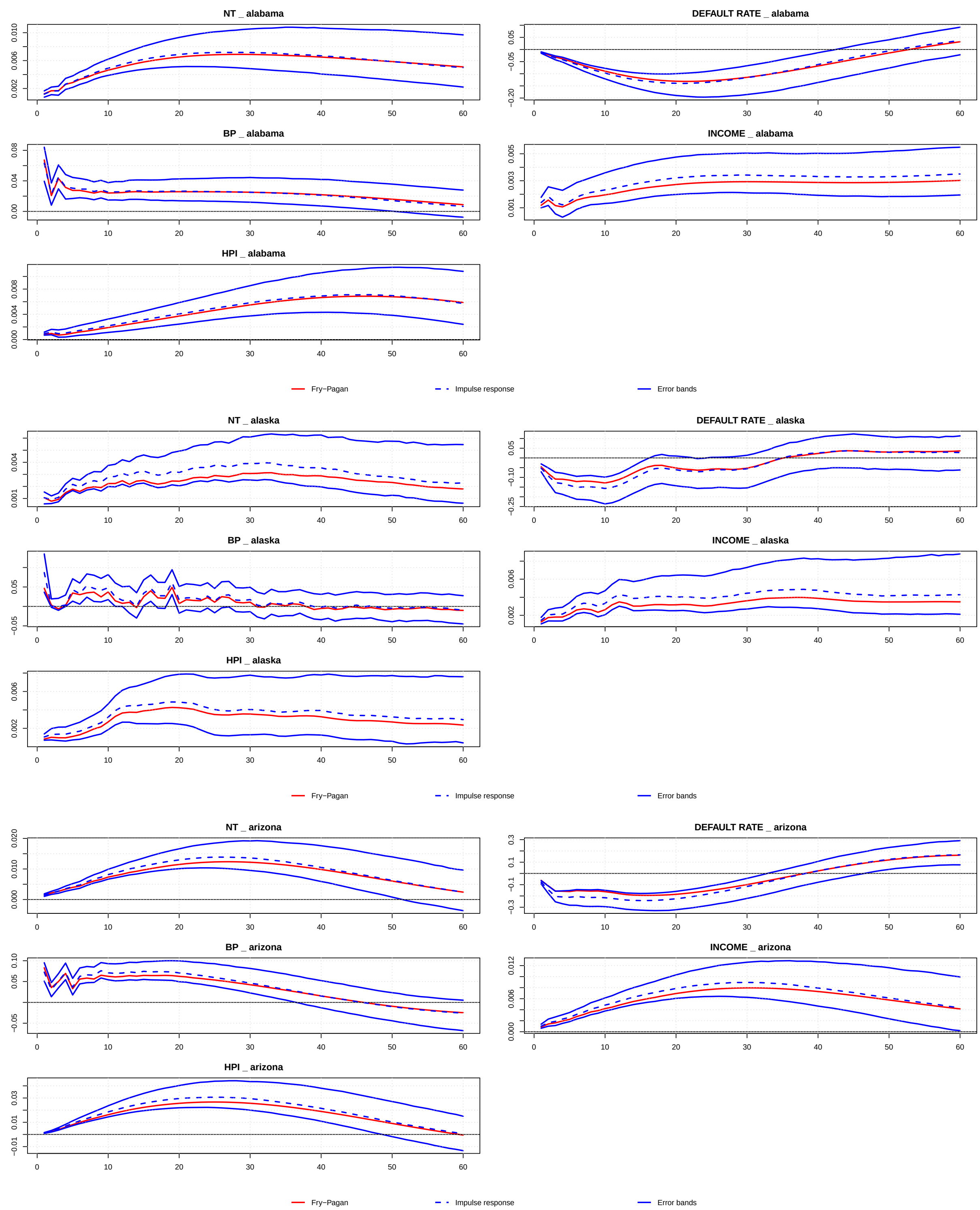
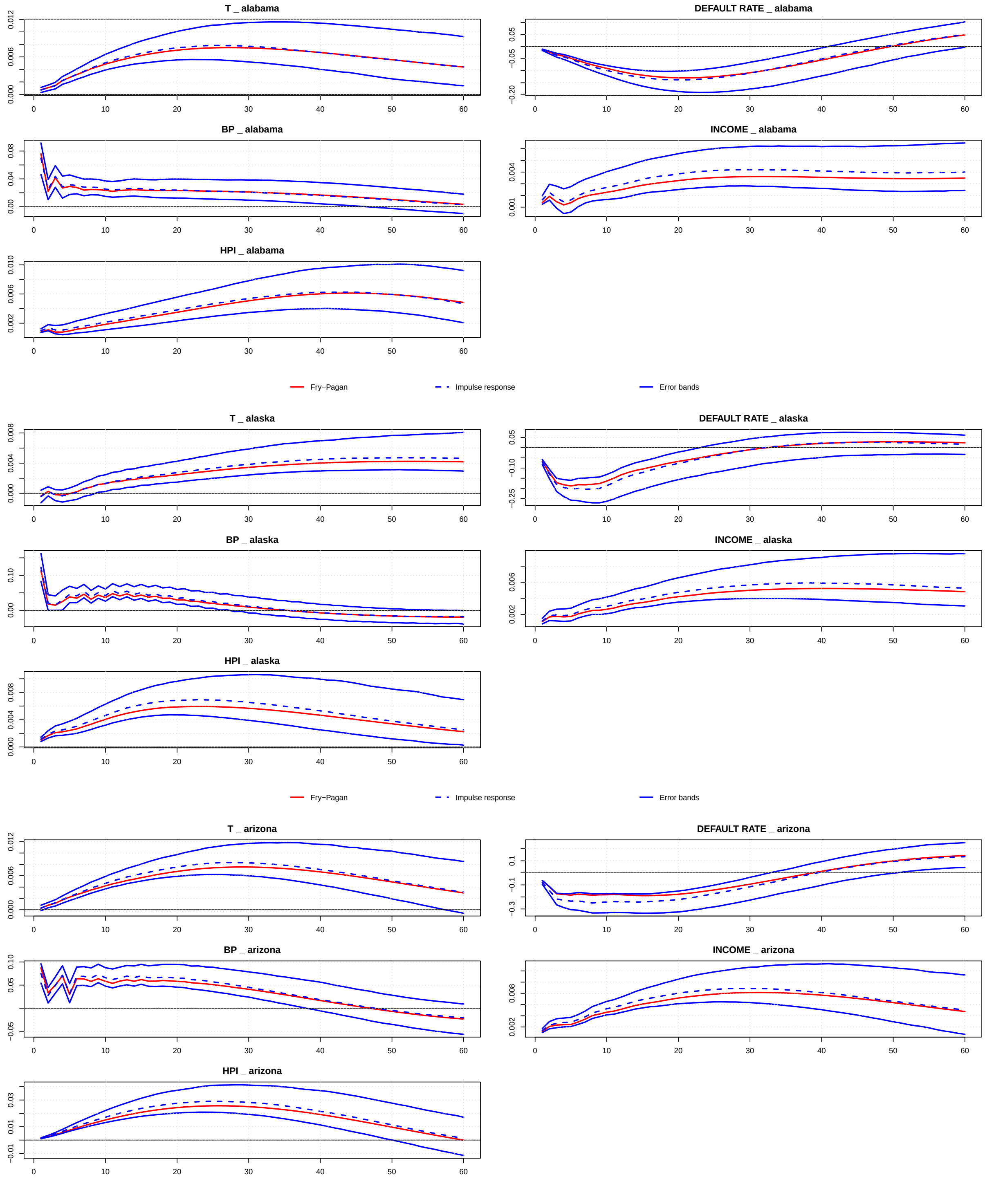

Impulse Response
wisconsin
NT
T

Figure 3.6: Impulse Responses for NT: MT Approach



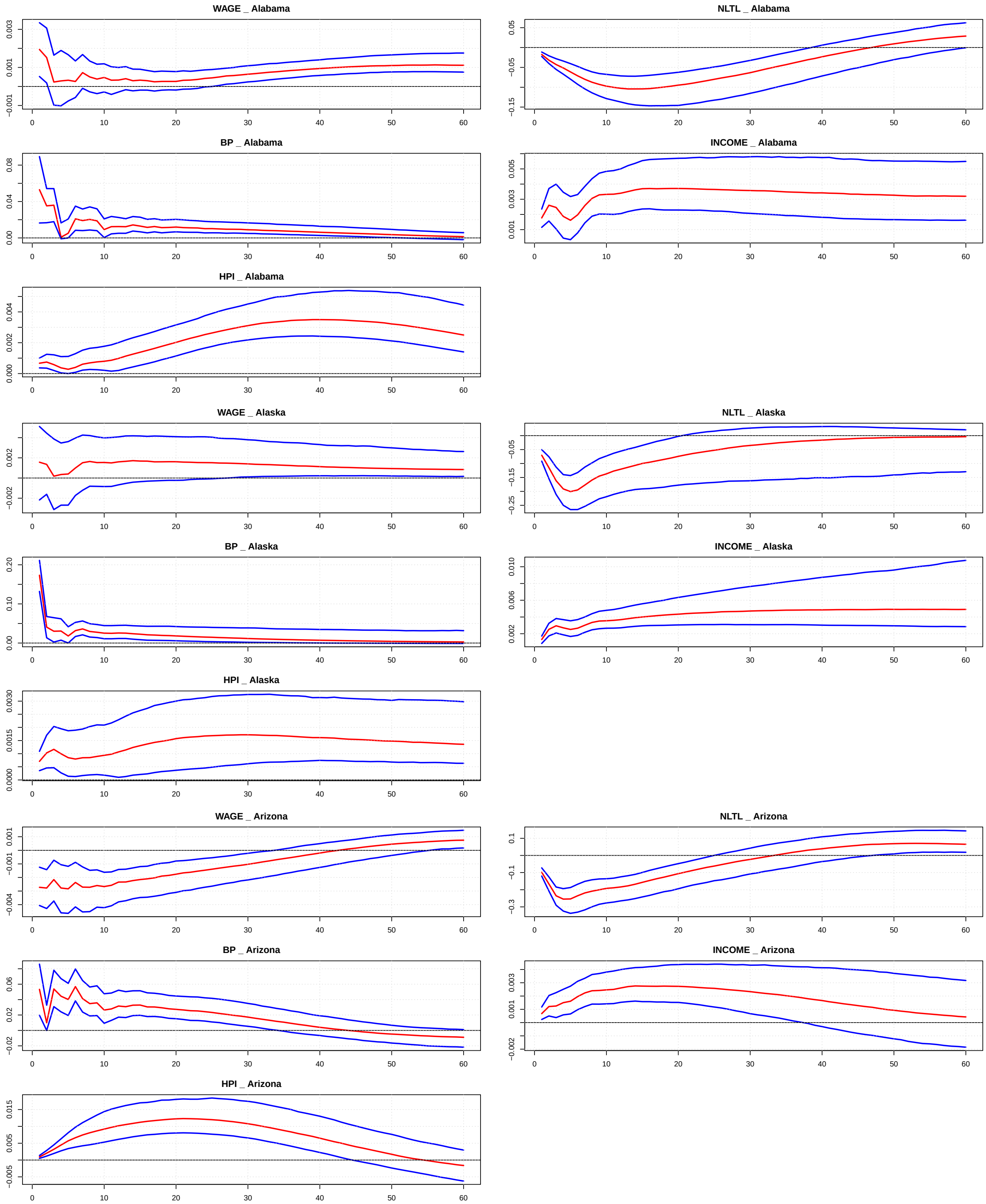
Notes: The graphs show the estimated MT and the penalty function for Non-Tradable (NT). The results for the rest of states are not reported to conserve space but available upon request.

Figure 3.7: Impulse Responses for T: MT Approach



Notes: The graphs show the estimated MT and the penalty function for Tradable (T). The results for the rest of states are not reported to conserve space but available upon request.

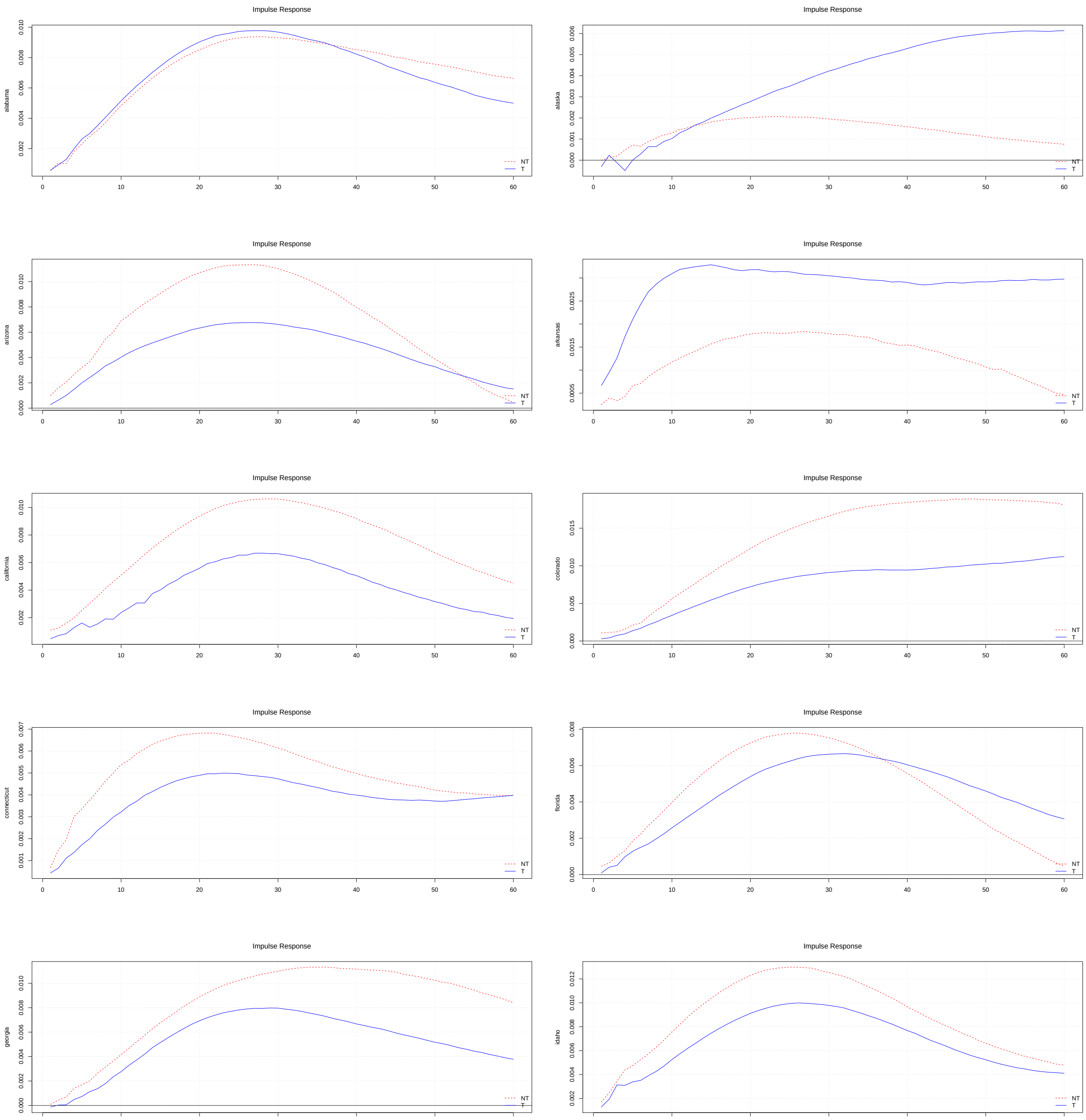
Figure 3.8: Impulse Responses for Wage



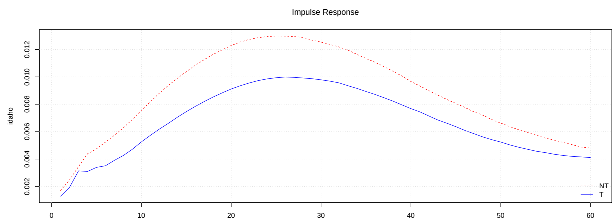
Notes: The graphs show the estimated impulse responses of wage to a positive house price shock. The results for the rest of states are not reported to conserve space but available upon request.

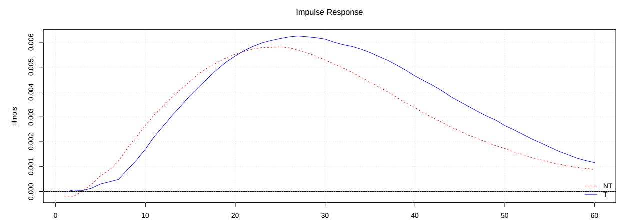
3.7 Appendix

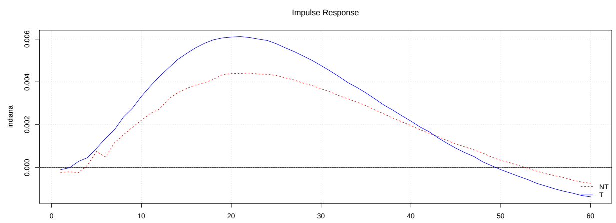
Figure 3.7.1: Impulse Responses for Four variables

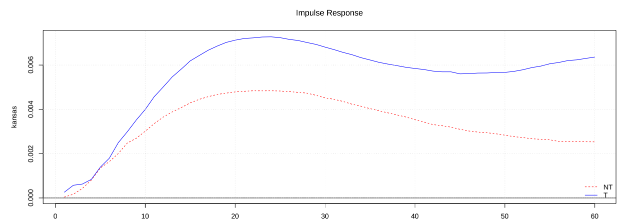


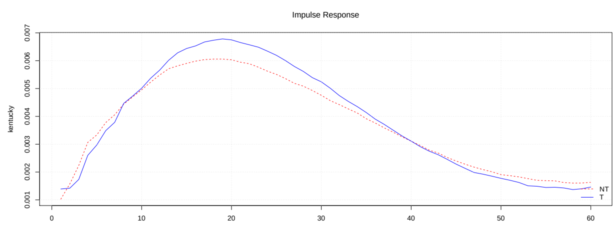
Notes: The graphs show the impulses responses for Tradable and Non-Tradable to the house price shock, when we remove income (I) from our baseline model.

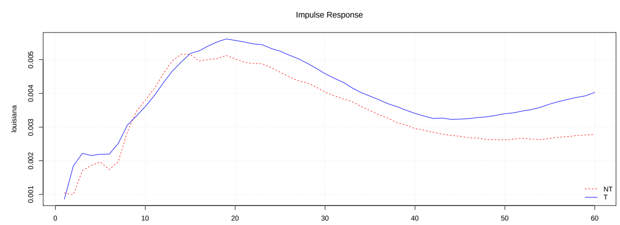

Impulse Response
idaho
0.002 0.004 0.006 0.008 0.010 0.012
0 10 20 30 40 50 60
NT
T

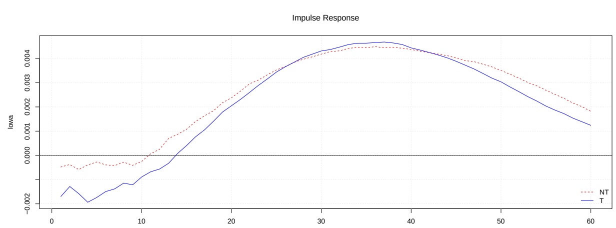

Impulse Response
illinois
0.000 0.001 0.002 0.003 0.004 0.005 0.006
0 10 20 30 40 50 60
NT
T

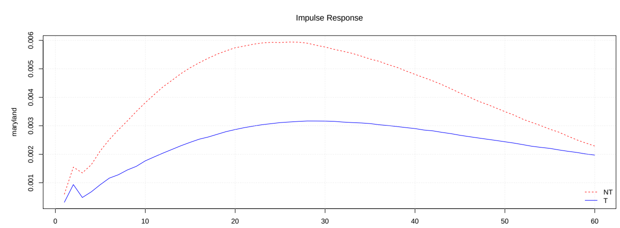

Impulse Response
indiana
0.000 0.002 0.004 0.006
0 10 20 30 40 50 60
NT
T

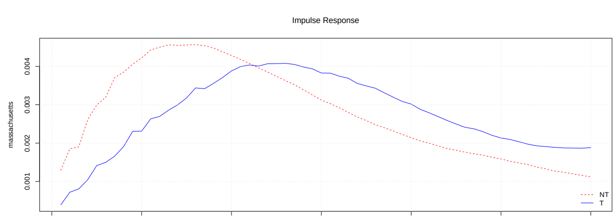

Impulse Response
kansas
0.000 0.002 0.004 0.006
0 10 20 30 40 50 60
NT
T


Impulse Response
kentucky
0.001 0.002 0.003 0.004 0.005 0.006 0.007
0 10 20 30 40 50 60
NT
T


Impulse Response
louisiana
0.001 0.002 0.003 0.004 0.005
0 10 20 30 40 50 60
NT
T


Impulse Response
iowa
−0.002 0.000 0.001 0.002 0.003 0.004
0 10 20 30 40 50 60
NT
T


Impulse Response
maryland
0.001 0.002 0.003 0.004 0.005 0.006
0 10 20 30 40 50 60
NT
T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massachusetts
0.001 0.002 0.003 0.004
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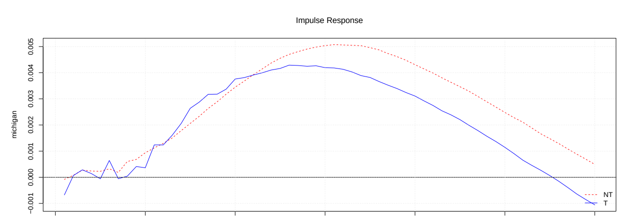
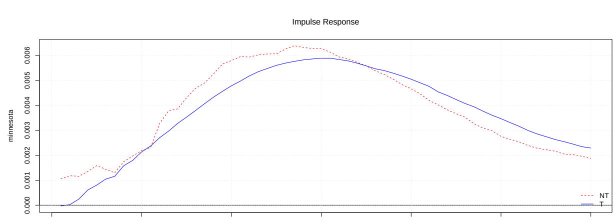
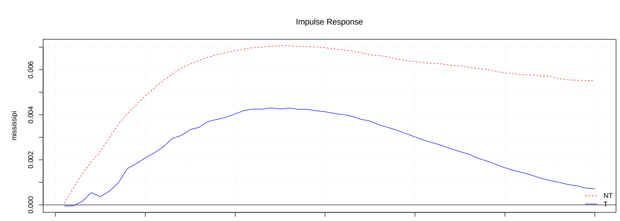
NT
T


Impulse Response
michigan
−0.001 0.000 0.001 0.002 0.003 0.004 0.005
0 10 20 30 40 50 60
NT
T


Impulse Response
minnesota
0.000 0.001 0.002 0.003 0.004 0.005 0.006
0 10 20 30 40 50 60
NT
T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missisipi
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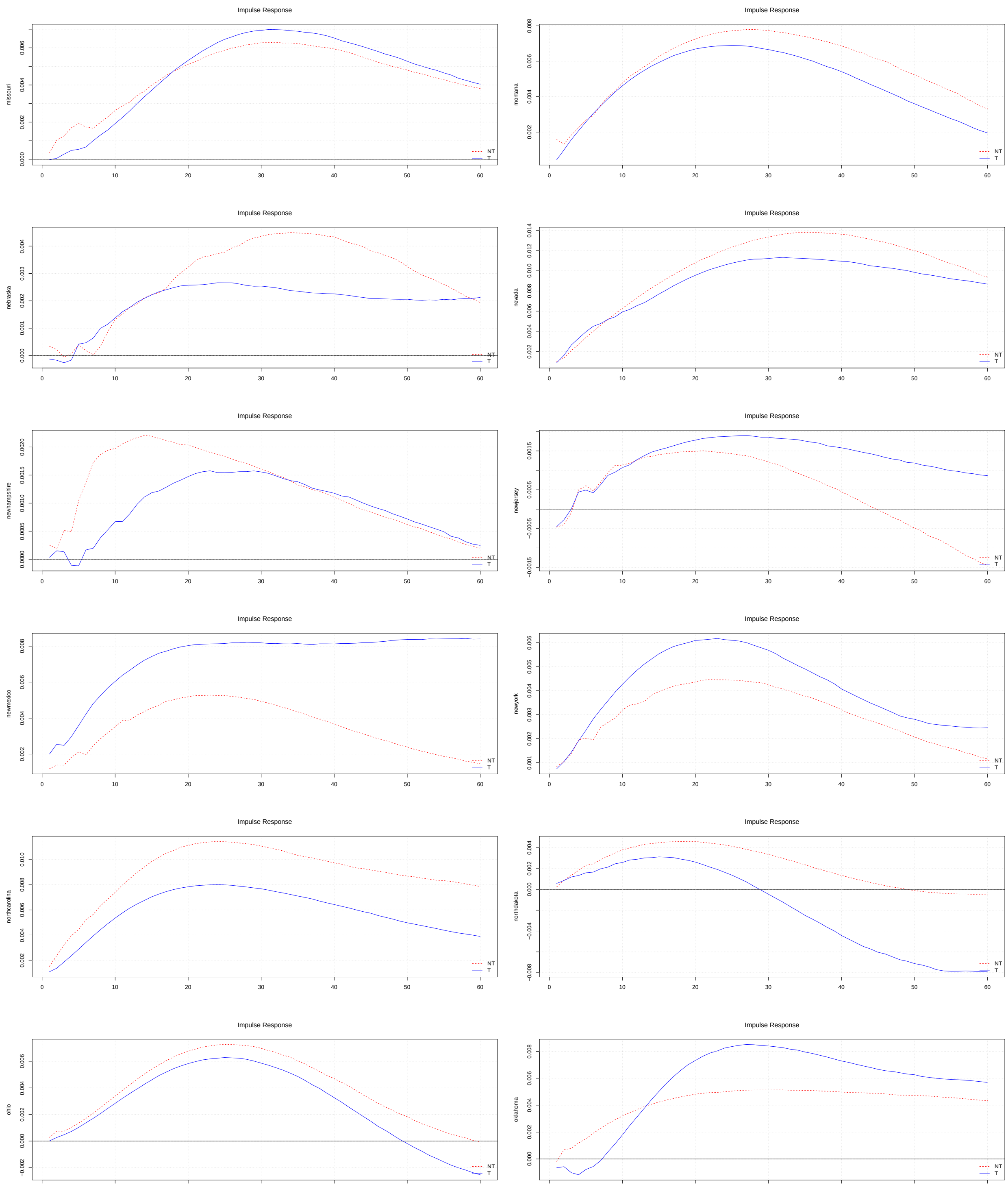
NT
T


Impulse Response
missouri
Impulse Response
montana
Impulse Response
nebraska
Impulse Response
nevada
Impulse Response
newhampshire
Impulse Response
newjersey
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Impulse Response
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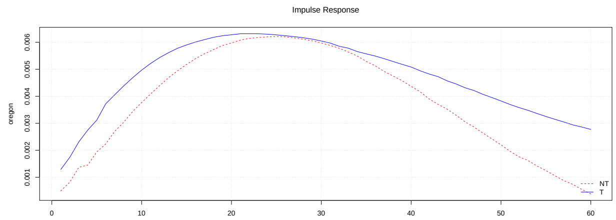
Impulse Response
oklahoma
NT
T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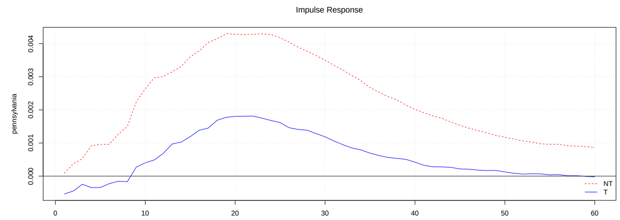
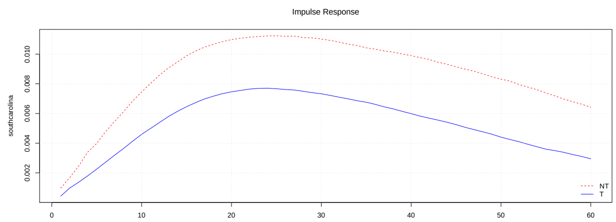
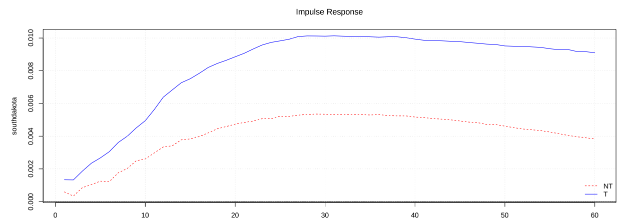
oregon
NT
T


Impulse Response
pennsylvania
NT
T


Impulse Response
southcarolina
NT
T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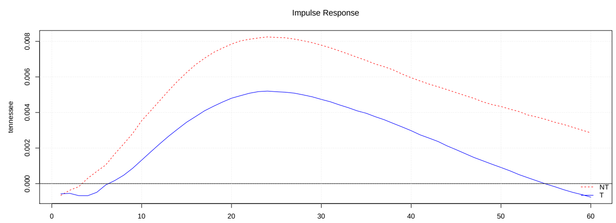
NT
T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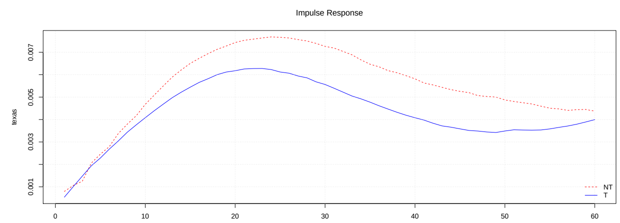
tennessee
NT
T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texas
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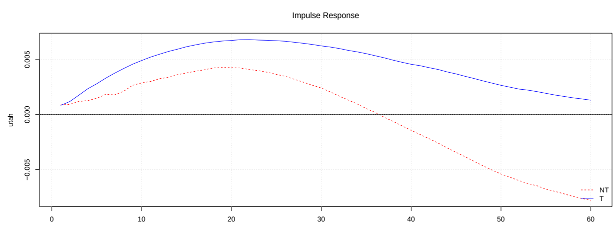
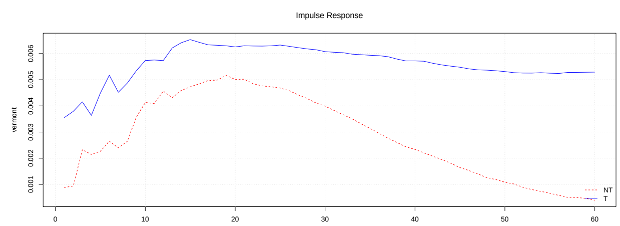
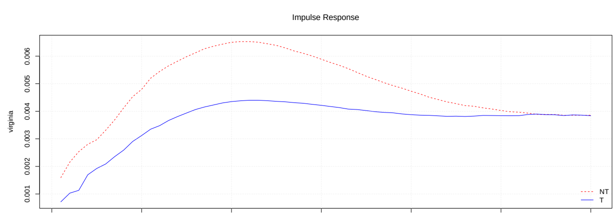
T


Impulse Response
utah
NT
T


Impulse Response
vermont
NT
T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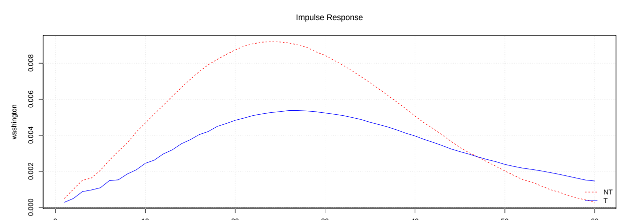
virginia
NT
T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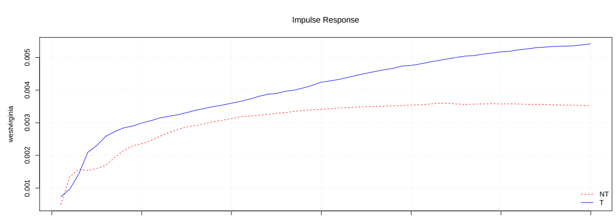
washington
NT
T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westvirginia
NT
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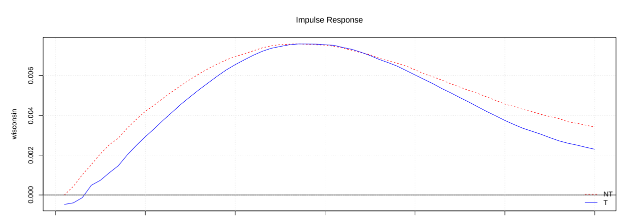

Impulse Response
wisconsin
NT
T

Chapter 4

Expectation of Future Income Growth and Housing Return: Evidence from the Present-Value Model

4.1 Introduction

The housing market, through the wealth effect, can impact a household's spending and thus, most homeowners consider the housing market as one way to invest. The recession of 2000 was followed by a collapse in the stock market, during which house prices rose and aggregate consumption did not decrease. This led to considering the housing market an alternative for investment. Also, negative shocks from the housing market during 2006-2009 led to a run on the shadow banking system and a large decline in real economic activities.[1] Because the housing market was at the center of the financial turmoil, understanding the housing market's fluctuations is a central goal for many researchers, policy-makers, and regulators.

What factors explain the fluctuations of the housing market? Looking at the house price growth is often the first step to understanding whether house prices are high enough. The problem with the price index is that it cannot be used to compare price levels across countries and also does not show whether fundamental factors or a price bubble are the reasons behind price fluctuations. The second factor is the house price-to-rent ratio,

[1] See Gorton (2009)

which reflects the relative costs of buying a house versus renting. The price-to-rent index cannot explain the boom and bust across countries because it is not standardized to the same representative apartment. Furthermore, there is a data limitation across countries.[2] The house price-to-income ratio method is commonly used as an appropriate first step in housing affordability assessment to generally identify the housing market fluctuations and capture the common trends of the housing market. For each country, this indicator can explain housing costs relative to the ability to pay. The relationship between house prices and income has been used widely to explain housing market dynamics, and the fluctuation of those can help to determine bubbles.

The focus of this paper is using information on the price-income ratio to explain the movements in housing market in 21 OECD countries. I use the present value model for the house price-income ratio to explain the household's expectations about future real price growth and future real income growth. This is based on the assumption that movements in price-income ratio reflects forward-looking agent's expectation about future movements in income growth and housing return. The idea of the present-value model for asset price goes back to Campbell and Shiller (1988a), and it has been applied in the housing market. [3] The present-value model implies that the log of housing prices to income ratio can be equaled to the expected discounted sum of the future income growth and the future housing price growth.

In the housing literature, the VAR model and co-integration are commonly applied when examining the long-run relationship between house price growth and income growth by using information from the price-income ratio. While the present value of price-income ratio is not stationary and the house price growth and the income growth are stationary [4], using VAR models is not suitable to capture the role of expected income growth and the housing returns or the movements in price-income ratio.[5] By modifying the present value model that includes a non-stationary component, we can capture

[2] SeeHimmelberg et al. (2005) for the problems associated with the price-rent ratio and price index.

[3] Campbell and Shiller (1988a) explains that in the finance literature, this model is the dynamic version of the Gordon growth model.(Campbell et al., 2009)

[4] See Table 1

[5] Abraham and Hendershott (1994), Malpezzi (1999), Capozza et al. (2002), Meen (2002) assumes that house prices and fundamentals are co-integrated, while Poterba et al. (1991) implicitly assume that they are not.

features such as transaction cost, differential tax, and differential regulation structure can be captured. To decompose the present value of the house price-income ratio, an unobserved component model is used that Kishor and Morley (2015) suggests to capture non-stationary components, expected income growth, and expected housing returns.

The results from the state space model suggest that the expected house price growth is more persistent than the expected income growth for all countries except for Spain. The results are consistent with Binsbergen et al. (2010), Kishor and Morley (2015), and Pástor and Stambaugh (2009), who have found the expected asset return is highly persistent. I find that the standard deviation of the shock to the non-stationary is larger than the standard deviation of the shock to the expected income growth and housing returns. Also, the results show a positive correlation between expected housing returns and income growth across all countries except Australia. These results are consistent with Abraham and Hendershott (1994), Malpezzi (1999), Capozza et al. (2002), Meen (2002). In addition, the correlation between expected housing return and non-stationary components is positive and high, which can be explained by different regulations across all countries.

This paper is related to a number of studies on the relationship between the housing markets and fundamental factors. A series of empirical studies by Mian and Sufi (2009, 2011, 2012) and Mian et al. (2013) show the impact of the housing market on macroeconomic expenditures during the recent financial crisis. Lai and Van Order (2010), Wang and Brand (2015), and Gallin (2006) show the relationship between income and house prices by using information from price-income ratios. Abraham and Hendershott (1994), Malpezzi (1999), Capozza et al. (2002), Meen (2003), and Gallin (2003) consider the long-run relationship between house prices and income by estimating an error-correction specification.

In the finance literature,it is common to use the present value model to explain households' expectations about the future.[6] Campbell and Shiller (1988a,b) use this approach to estimate housing returns. In this paper, I use the present value model for the house price-income ratio to specify future income growth and housing returns. This

[6]The present value model is widely used in asset markets. For example, Bernanke and Kuttner (2005); Campbell and Ammer (1993); Shiller and Beltratti (1992); Vuolteenaho (2002)

paper is related to Kishor and Morley (2015) that used the state-space model to modify the present-value model of the price-rent ratio for the housing market in 18 U.S. metropolitan areas.

The remainder of this paper is structured as follows. In section 2, a modified present-value model is presented. Section 3 describes the data and discusses the empirical results. Section 4 provides a conclusion.

4.2 Model Specification

4.2.1 Modified Present-value Model

The present-value model for asset prices has been used commonly in the finance literature to study the behavior of equity markets. The present value model of the price income is:

$$p_t - y_t = k/(1-\rho) + \sum_{i=0}^{\infty} \rho^{i-1} E_t(\triangle y_{t+j} - \triangle p_{t+i}) \tag{4.1}$$

The present price-income ratio explains a household's expectations about future house price growth and future income growth. As expected, income growth and expected price growth are stationary, while the price-income ratio should be stationary. Table 1 shows that the expected income growth and expected price growth are stationary, while the price-income ratio has unit roots. Kishor and Morley (2015) suggest a modified present-value model of the housing markets to capture non-stationary components. Transaction cost, differential tax, and differential regulation structure for each country can be explained by non-stationary factors.

Based on the modified present-value model, I decompose the price-income ratio into the current expected income growth and expected price growth, which are stationary, and a residual component(Z), which is non-stationary. By applying an unobserved component approach, I assume that expected income growth and expected price growth are AR(1) and the non-stationary component (Z) is a random walk. In this model, expected income growth, expected housing return, and Z component are talent variables, while information is used from past realized income growth, realized housing return, and price-income ratio.

A modified present-value model of Campbell and Shiller (1988a) for the price-income can be written as:

$$p_t - y_t = M + \gamma_1 \triangle y_t^e + \gamma_1 \triangle p_t^e + Z_t \tag{4.2}$$

where $p_f - r_t$ as the log price-income ratio,$\triangle r_t^e$ represents the expected income growth, $\triangle p_t^e$ is the expected price growth, and Z_t is the non-stationary component.

To estimate a modified present-value model, I develop an unobserved component approach for multi variables. I define three measurement equations such as:

$$p_t - y_t = \mu + \gamma_1 \triangle y_t^e + \gamma_2 \triangle p_t^e + Z_t \tag{4.3}$$

$$\triangle y_{t+1} = \triangle y_t^e + \varepsilon_{t+1}^y \tag{4.4}$$

$$\triangle p_{t+1} = \triangle p_t^e + \varepsilon_{t+1}^p \tag{4.5}$$

As suggested by Cochrane (2008), I need to impose restrictions on the covariance structure in the above state space model to achieve identification. I follow Binsbergen et al. (2010)'s identification strategy and assume that covariance between shocks to realized variables are uncorrelated with the shocks to unobserved state variables. The measurement equation has the following variance-covariance matrix:

$$R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \sigma_y^2 & \sigma_{yp} \\ 0 & \sigma_{yp} & \sigma_p^2 \end{bmatrix}$$

Three transition equations are specified as the expected real income growth and the expected real price growth are AR(1), while the present-value residual is a random walk specification.

$$\triangle y_t^e = \delta_1 + \beta_1 \triangle y_{t-1}^e + \varepsilon_t^{y^e} \tag{4.6}$$

$$\triangle p_t^e = \delta_2 + \beta_2 \triangle p_{t-1}^e + \varepsilon_t^{p^e} \tag{4.7}$$

$$Z_{t+1} = \gamma_3 + Z_t + \varepsilon_t^Z \tag{4.8}$$

The transition equation has the following variance-covariance matrix:

$$Q = \begin{bmatrix} \sigma_{y^e}^2 & \sigma_{y^e p^e} & \sigma_{y^e z} \\ \sigma_{y^e p^e} & \sigma_{p^e}^2 & \sigma_{p^e z} \\ \sigma_{y^e z} & \sigma_{p^e z} & \sigma_z^2 \end{bmatrix}$$

To estimate this state space model, I adopt the Kalman Filter simulation.

4.2.2 Variance Decomposition of the present-value level

It is important to explain what moves the price-income ratios in the housing market. One way to do that is to use a variance decomposition of the present value level of price-income ratio for equation(2):

$$var(p_t^* - y_t^*) = \gamma_1^2 var(\triangle y_t^e) + \gamma_2^2 var(\triangle p_t^e) + 2\gamma_1\gamma_2 cov(\triangle y_t^e, \triangle p_t^e) \tag{4.9}$$

The variation of the present-value level of the price-income ratio $p_t^* - y_t^*$ is explained by expected real income growth ($\gamma_1^2 var(\triangle y_t^e)$), and the percentage of variation is explained by the expected housing price growth($\gamma_2^2 var(\triangle p_t^e)$).

4.3 Data and Empirical Results

4.3.1 Data

I use quarterly data for 21 countries and sample runs from 1975:Q1 through 2015:Q1. The data on the housing price index expressed in real terms (RHPI) and the personal disposable income expressed in real terms (RPDI) index are from the Federal Reserve Bank of Dallas, Texas. For each country, the housing price index is consistent with the quarterly U.S. housing price index for existing single-family houses.[7] All variables in real terms are deflated with the personal consumption expenditure (PCE) deflater. Figures 1,2, and 3 present the trend of these variables. After being seasonally adjusted, I calculate the price-income ratio for my model. Figures 4, 5, and 6 show the trend of the price-income ratio for 21 countries.

4.3.2 Empirical results

As a first step, I test whether the price-income ratio has satisfied a unit root test. Table 1 suggests that the price-income ratio is not stationary, while the realized income growth and realized price growth are stationary for all countries.These results support my assumption for a modified present value model of price-income ratio.

I estimate the modified present-value model by using the Kalman Filter for a state-space model. My results of parameter estimations for equation(2)-(5) are reported in Tables 2, 3, and 4. The results of drift show that $\delta 1$ for all countries is positive, with $\delta 2$ for Japan, Italy, Spain, Germany being negative, $\delta 3$ for S. Africa, Luxembourg, Japan, Italy, Finland, Switzerland, and Belgium being positive. The results from the parameter(AR coefficient β) suggest that expected real income growth is less persistent than the expected housing price growth.

Table 2 shows that the measurement coefficient γ_2 is negative, while the γ_1 for all countries is positive. These results suggest that an increase in expected real income growth leads to a price-income ratio increase, and an increase at expected housing price causes an increase in the price-income ratio.

The results of the standard deviations of expected income growth σ_{y^e}, expected price growth σ_{p^e} and the Z component σ_z are presented in Table 3. According to these results, the standard deviation of shocks to the Z component is larger than the standard deviation of the expected housing price growth and the expected income growth. The standard

[7] A detailed description of the sources and methodology for this data can be found in Mack et al. (2011)

deviation of shock to the realized price growth is higher than the realized income growth, yet the standard deviation of shock to the realized price growth is less than the realized income price for Italy and New Zealand.

The results of the correlation between expected income growth and expected price growth are presented in Table 4. For all countries except Australia and South Africa, the correlation between expected income and price ($\rho_{y^e p^e}$) is positive. These results are expected because a shock to the expected income growth increases the expected price growth. The result for France shows that the correlation is high where the expected price growth increased, while at the same time, the expected income growth increased. For other countries,the results suggest that the expected price growth will increase when income increases, but not at same time or close to it. The results also show there is a positive correlation between expected price growth and the residual component. France has the highest correlation, while Japan has the lowest. I also find the correlation between expected income growth and the residual component is positive for Switzerland, France, UK,Italy, Japan,South Korea, Netherlands, Norway, New Zealand and Sweden. The results suggest that the correlation between realized income and price growth is positive for all countries except Australia, Switzerland, Denmark, Japan and South Africa.

To understand which component has a more important role in the price-income ratio, I perform a variance decomposition. Table 5 and 6 present results for the variance decomposition test. The findings suggest that most of the variation in the present-value component is explained by expected price growth for all countries. Australia and South Africa have the highest shares of income among all countries, which is about 11%. My results also show that shares of the expected house price growth for most countries is higher than 100%, except for Australia, Belgium, Canada, Spain, France, Ireland, US and South Africa, which are close to 100%. For countries in which this share is higher than 100%, the negative share of the covariance diminishes the overall variation in the price-income ratio.

4.3.3 Robustness Check

In this part, I use a robustness check to identify the structure of my model. I define five models and then compare their log likelihood. First, if I have no correlation between expected income and price growth and residual components, then there is no correlation between realized income and price growth. Second, there is only a correlation between realized price and income growth. Third, there is a correlation between realized income and price growth and a correlation between expected income and price growth. Fourth, I do not have a correlation between realized income and price growth. Finally, if I define the baseline model, which considers the correlation between realized income and price growth, there is an expected correlation between income and price growth. Table 7 shows the robustness results, which reveal that for all countries, the baseline model has a higher log likelihood than the other models. The robustness test suggests the baseline model is much better than the other models.

4.4 Conclusion

In this paper, by using the state space model, I modified the present-value model to consider the price-income ratio as a metric of affordability indicator for 21 OECD countries. I explained that the price-income ratio may move due to a change in expected income and price growth, which are stationary, and the residual component, which is non-stationary.

I find that both expected income growth and expected price growth are significant in explaining movements in the price-income ratio. In addition, I find that the residual component that may explain the regulation and structural feature of the housing market is also significant, while for all countries, there is a significant heterogeneity. My findings suggest that the correlation between expected income and the residual component is positive for all countries. I also use variance decomposition, which shows the share of price is higher than 100%, while my results from the share of correlation are negative. I also present a robustness check to identify the correlation between expected income, price growth and the residual component, as well as for the correlation between realized income and price. My results show that when I consider all correlations, I will have a higher log likelihood.

Table 4.4.1: Unit Root Test

	ADF			PP		
	Ratio(price-Income)	Δy_t	Δp_t	Ratio(price-Income)	Δy_t	Δp_t
Australia	0.53	0.00	0.00	0.28	0.01	0.01
Belgium	0.35	0.00	0.00	0.93	0.01	0.13
Canada	0.40	0.00	0.00	0.41	0.01	0.01
Switzerland	0.09	0.00	0.00	0.93	0.01	0.07
Germany	0.46	0.00	0.00	0.95	0.01	0.01
Denmark	0.11	0.00	0.00	0.56	0.01	0.01
Spain	0.04	0.00	0.00	0.73	0.01	0.01
Finland	0.01	0.00	0.00	0.55	0.01	0.01
France	0.67	0.00	0.00	0.88	0.01	0.01
UK	0.52	0.00	0.00	0.69	0.01	0.01
Ireland	0.13	0.00	0.00	0.92	0.02	0.07
Italy	0.01	0.00	0.00	0.01	0.01	0.01
Japan	0.08	0.00	0.00	0.98	0.01	0.04
S. Korea	0.60	0.00	0.00	0.91	0.01	0.01
Luxembourg	0.67	0.00	0.00	0.90	0.01	0.01
Netherlands	0.13	0.00	0.00	0.89	0.01	0.01
Norway	0.18	0.00	0.00	0.57	0.01	0.01
New Zealand	0.63	0.00	0.00	0.18	0.01	0.01
Sweden	0.02	0.00	0.00	0.90	0.01	0.01
US	0.28	0.00	0.00	0.75	0.01	0.01
S. Africa	0.36	0.00	0.00	0.75	0.01	0.01

Note: Δy_t and Δp_t represent the real income growth and the real price growth respectively. ADF and PP also represent the Argument Dicky Fuller's and Phillips-Peron's tests.

Table 4.4.2: Parameter Estimation

countries	$\delta 1$	$\delta 2$	$\beta 1$	$\beta 2$	$\gamma 1$	$\gamma 2$
Australia	0.0494	-0.0678	0.3236	0.5884	0.2977	-0.3863
	0.0685	0.0258	0.0761	0.0713	0.0462	0.0321
Belgium	-0.0373	-0.0336	0.6867	0.9057	0.1413	-0.6448
	0.0535	0.0146	0.0557	0.0326	0.0145	0.2010
Canada	-0.0019	-0.0366	-0.2181	0.5939	-0.3209	-0.6729
	0.0619	0.0172	0.0759	0.0680	0.1336	0.0551
Switzerland	0.0179	0.0096	0.7186	0.8916	0.1558	-0.8141
	0.0449	0.0076	0.0637	0.0304	0.0285	0.2017
Germany	-0.0332	0.1312	0.0700	0.6533	0.5558	-0.1482
	0.0839	0.0343	0.0548	0.0586	0.4040	0.0118
Denmark	-0.0094	-0.0146	0.2460	0.6090	0.2619	-0.6207
	0.0718	0.0140	0.0755	0.0627	0.0536	0.0379
Spain	0.0047	0.0492	0.6450	0.3693	0.1182	-0.7090
	0.0575	0.0261	0.1019	0.0823	0.0306	0.0692
Finland	-0.0010	0.0063	0.3457	0.7417	0.4176	-0.8229
	0.0651	0.0141	0.0727	0.0451	0.0457	0.0947
France	0.0027	-0.0358	0.1653	0.7975	0.2939	-0.4500
	0.1153	0.0162	0.0949	0.0508	0.1319	0.0852
UK	-0.0083	-0.0362	0.7092	0.7300	-0.1405	-0.4083
	0.0190	0.0112	0.1081	0.0526	0.1294	0.0811
Ireland	0.0108	-0.0075	0.8651	0.9216	0.2664	-1.2207
	0.0377	0.0085	0.0375	0.0348	0.0647	0.4893
Italy	-0.0144	0.0284	0.2679	0.6386	0.3778	-0.7389
	0.0736	0.0179	0.0722	0.0549	0.0644	0.0563
Japan	-0.0085	0.0348	0.4770	0.9157	0.1203	-0.6069
	0.1173	0.0167	0.0715	0.0314	0.0062	0.2031
S. Korea	0.0145	0.1239	0.5816	0.6825	0.1292	-0.1954
	0.0613	0.0339	0.0702	0.0555	0.0073	0.0183
Luxembourg	0.0105	-0.0498	0.6200	0.7090	0.2355	-0.4063
	0.0553	0.0276	0.0694	0.0525	0.0164	0.0438
Netherlands	-0.0062	-0.0407	0.2681	0.6721	0.2257	-0.4504
	0.0937	0.0213	0.0680	0.0604	0.0368	0.0399
Norway	-0.0130	-0.0057	0.1866	0.4349	0.5244	-0.6216
	0.0682	0.0217	0.0798	0.0707	0.1777	0.0255
New Zealand	0.0085	-0.0276	0.5837	0.7701	0.2240	-0.5411
	0.0583	0.0180	0.0564	0.0367	0.0090	0.0595
Sweden	-0.0016	-0.0019	0.7138	0.8622	0.2223	-0.9024
	0.0490	0.0092	0.0710	0.0375	0.0388	0.2065
US	-0.0212	0.0130	0.2289	0.8304	0.5216	-0.8548
	0.0687	0.0105	0.0797	0.0479	0.1389	0.2030
S. Africa	-0.0055	-0.0019	0.6407	0.8359	0.4280	-0.9530
	0.0550	0.0161	0.0605	0.0622	0.0355	0.3305

Note: y^e and p^e refer to expected real income growth, and expected housing price growth and Z is the deviation from the present-value components.$\delta 1$, $\delta 2$ and $\delta 3$ are constant in AR(1). $\beta 1$ and $\beta 2$ are coefficients in AR(1),$\gamma 1$ and $\gamma 2$ refer to the estimated coefficients of the measurement equation.

Table 4.4.3: Parameter estimation

countries	σ_{y^e}	σ_{p^e}	σ_z	σ_y	σ_p
Australia	0.0075	0.0149	0.0723	0.0001	0.0076
	0.000419	0.002027	0.010069	0.00051	0.0026
Belgium	0.0065	0.0064	0.0678	0.0017	0.0018
	0.0004	0.0006	0.0105	0.0004	0.0010
Canada	0.0104	0.0176	0.0571	0.0013	0.0055
	0.0006	0.0018	0.0079	0.0018	0.0042
Switzerland	0.0041	0.0055	0.0408	0.0001	0.0007
	0.0003	0.0034	0.0116	0 .0001	0.0006
Germany	0.0072	0.0033	0.0495	0.0023	0.0042
	0.0005	0.0006	0.0102	0.0008	0.0005
Denmark	0.0054	0.0215	0.0551	0.0087	0.0008
	0.0015	0.0012	0.0088	0.0010	0.0024
Spain	0.0056	0.0344	0.0780	0.0007	0.0205
	0.0003	0.0054	0.0107	0.0006	0.0072
Finland	0.0065	0.0104	0.0632	0.0104	0.0083
	0.0010	0.0012	0.0171	0.0007	0.0010
France	0.0076	0.0054	0.0612	0.0010	0.0048
	0.0004	0.0006	0.0197	0.0008	0.0005
UK	0.0077	0.0147	0.0712	0.0001	0.0049
	0.0004	0.0014	0.0134	0.0001	0.0022
Ireland	0.0037	0.0098	0.0916	0.0002	0.0051
	0.0002	0.0010	0.0308	0.0001	0.0011
Italy	0.0093	0.0187	0.0531	0.0044	0.0025
	0.0008	0.0011	0.0081	0.0012	0.0018
Japan	0.0041	0.0044	0.0633	0.0001	0.0017
	0.0002	0.0004	0.0065	0.0001	0.0005
S. Korea	0.0128	0.0149	0.1227	0.0066	0.0104
	0.0010	0.0024	0.0125	0.0013	0.0024
Luxembourg	0.0097	0.0088	0.0508	0.0014	0.0074
	0.0005	0.0010	0.0084	0.0005	0.0009
Netherlands	0.0106	0.0087	0.1098	0.0051	0.0123
	0.0009	0.0012	0.0340	0.0015	0.0010
Norway	0.0011	0.0218	0.0378	0.0109	0.0108
	0.0005	0.0012	0.0027	0.0006	0.0006
New Zealand	0.0096	0.0133	0.0601	0.0018	0.0006
	0.0005	0.0007	0.0103	0.0010	0.0016
Sweden	0.0071	0.0092	0.0679	0.0001	0.0057
	0.00403	0.0072	0.0228	0.0001	0.0006
US	0.0052	0.0045	0.0393	0.0002	0.0049
	0.0002	0.0006	0.0050	0.0002	0.0005
S. Africa	0.0019	0.0188	0.0599	0.0072	0.0090
	0.0007	0.0010	0.0114	0.0005	0.0009

Note: y^e and p^e refer to expected real income growth, and expected housing price growth and z is the deviation from the present-value components. $\delta1$, $\delta2$ and $\delta3$ are constant in AR(1). $\beta1$ and $\beta2$ are coefficients in AR(1) ,$\gamma1$ and $\gamma2$ refer to the estimated coefficients of the measurement equation.

Table 4.4.4: Correlation Estimation

countries	$\rho_{y^e p^e}$	$\rho_{y^e z}$	$\rho_{p^e z}$	ρ_{yp}
Australia	-0.0900	-0.4194	0.9331	0.9854
	0.0959	0.0926	0.0270	0.8670
Belgium	0.5747	0.3551	0.9690	0.9997
	0.0629	0.1180	0.0240	0.0297
Canada	0.1952	-0.0314	0.9568	0.9999
	0.0913	0.0953	0.0174	0.0023
Switzerland	0.4441	0.2292	0.9730	0.0001
	0.0737	0.1081	0.0183	0.0000
Germany	0.2912	-0.1820	0.8876	0.0002
	0.0723	0.1158	0.0444	0.0000
Denmark	0.1296	-0.0877	0.9726	0.0307
	0.0786	0.0897	0.0108	0.0000
Spain	0.0891	-0.1856	0.9621	0.9982
	0.0896	0.1097	0.0215	0.0488
Finland	0.5342	0.2497	0.9519	-0.0461
	0.0599	0.0935	0.0208	0.0000
France	0.1143	-0.0865	0.9798	0.9484
	0.0874	0.0924	0.0111	0.0000
UK	0.8925	0.7745	0.9765	0.0725
	0.0919	0.1410	0.0116	0.0000
Ireland	0.1906	-0.0686	0.9662	1.0000
	0.0923	0.1652	0.0345	0.0000
Italy	0.3770	0.1022	0.9534	0.0223
	0.0668	0.0865	0.0180	0.0000
Japan	0.1406	-0.0542	0.9801	0.9999
	0.0938	0.1090	0.0157	0.0012
S. Korea	0.5443	0.1324	0.9035	0.0233
	0.0722	0.1432	0.0466	0.0000
Luxembourg	0.1973	-0.3656	0.8403	0.0000
	0.0805	0.1353	0.0756	0.0000
Netherlands	0.2405	-0.0418	0.9597	0.9996
	0.0651	0.0580	0.0158	0.0000
Norway	0.1638	-0.1704	0.9441	0.0000
	0.0827	0.0898	0.0186	0.0000
New Zealand	0.4110	0.0050	0.9136	0.0000
	0.0571	0.0000	0.0226	0.0000
Sweden	0.4743	0.2680	0.9752	0.9997
	0.1002	0.1286	0.0171	0.0371
US	0.1731	-0.0662	0.9712	0.3563
	0.1001	0.1067	0.0160	0.0000
S. Africa	0.0132	-0.3406	0.9228	0.9999
	0.1248	0.1265	0.0530	0.0000

Note: $\rho_{y^e p^e}$, $\rho_{y^e z}$ and $\rho_{p^e z}$ refer to the correlation between expected real income growth and expected price growth, expected real income and residual component, and price growth and the residual component respectively. Standard errors are in parentheses.

Table 4.4.5: Share of unobserved components

countries	share of income	share of price	share of covariance
Australia	0.1311	0.8699	-0.0011
Belgium	0.0148	0.9815	0.0035
Canada	0.0260	0.9728	0.0010
Switzerland	0.0152	0.9806	0.0040
Germany	0.1021	0.8973	0.0004
Denmark	0.0229	0.9763	0.0007
Spain	0.0961	0.9030	0.0007
Finland	0.0391	0.9489	0.0119
France	0.0105	0.9892	0.0002
UK	0.0402	0.9552	0.0044
Ireland	0.0302	0.9630	0.0066
Italy	0.0361	0.9587	0.0050
Japan	0.0050	0.9946	0.0002
S. Korea	0.1812	0.8155	0.0032
Luxembourg	0.1961	0.7991	0.0047
Netherlands	0.0307	0.9681	0.0010
Norway	0.0988	0.8989	0.0022
New Zealand	0.0750	0.9174	0.0075
Sweden	0.0254	0.9655	0.0090
US	0.0162	0.9820	0.0016
S. Africa	0.0796	0.9194	0.0009

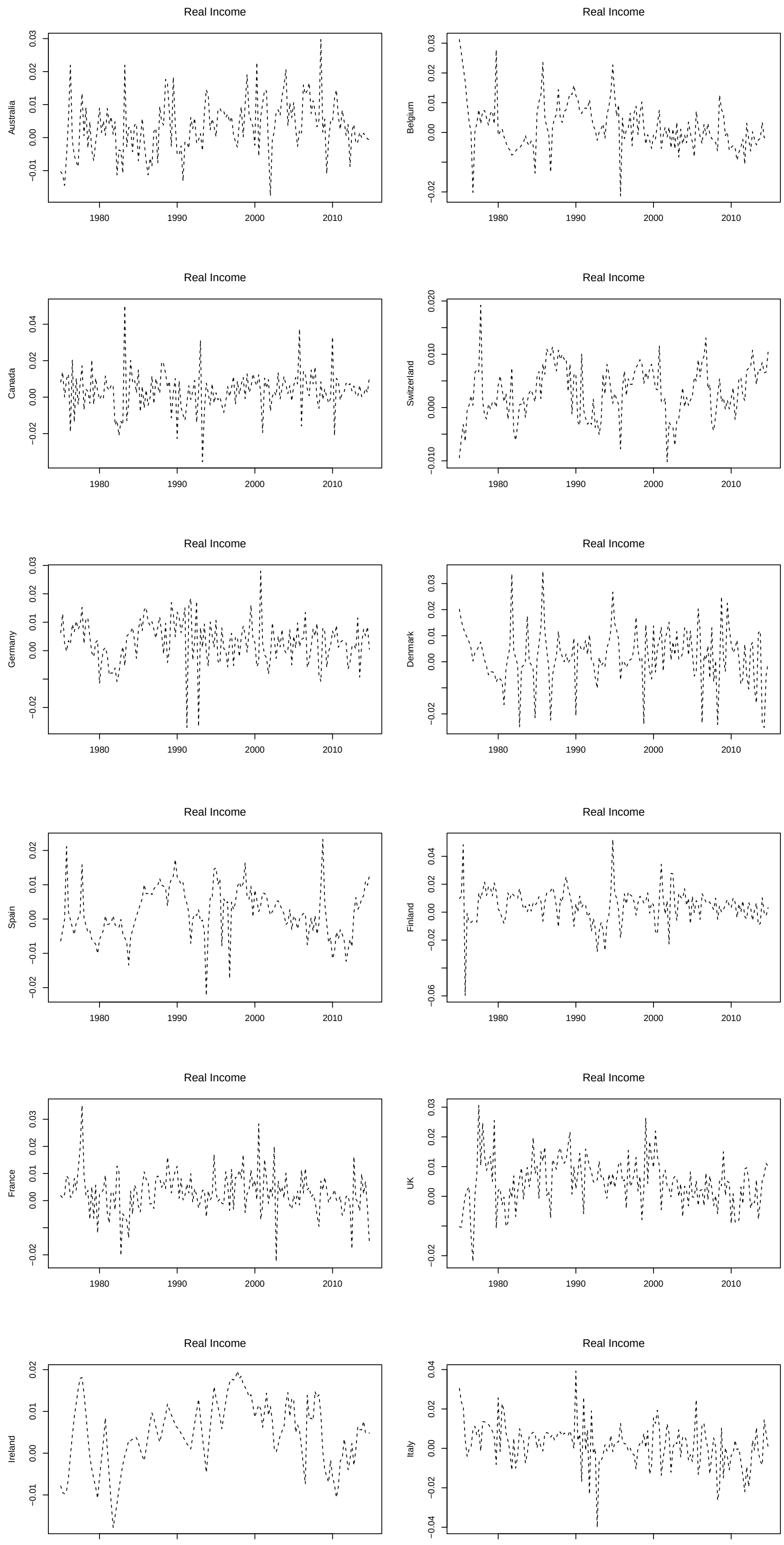
Note: In this table we present the share explained by expected income, price growth from the variance decomposition.

Table 4.4.6: Log likelihood value for alternative model specification

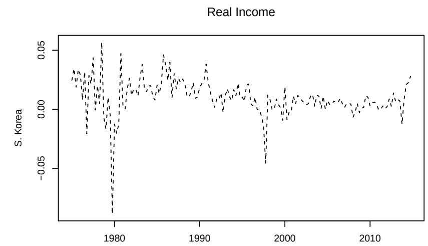
countries	Zero correlation	$\rho_{yp} \neq 0$	$\rho_{y^e p^e} \neq 0$ and $\rho_{yp} \neq 0$	$\rho_{yp} = 0$	Baseline Model
Australia	1206.418	1206.64	1206.67	1215.05	1215.09
Belgium	1379.16	1379.37	1404.90	1411.16	1412.02
Canada	1210.51	1213.16	1213.40	1244.64	1244.90
Switzerland	1710.59	1713.04	1729.38	1794.40	1794.79
Germany	1434.40	1442.56	1443.54	1445.57	1448.71
Denmark	1249.90	1250.05	1251.08	1377.18	1377.19
Spain	1120.66	1121.03	1122.25	1157.15	1157.97
Finland	1337.52	1365.81	1365.83	1503.59	1512.24
France	1419.36	1419.79	1419.95	1431.23	1431.76
UK	1268.69	1272.18	1276.00	1303.10	1303.39
Ireland	1435.78	1436.13	1437.13	1450.00	1452.43
Italy	1221.94	1233.24	1233.78	1262.88	1265.91
Japan	1490.62	1492.11	1496.15	1496.54	1496.77
S. Korea	973.15	982.35	987.80	988.66	991.02
Luxembourg	1261.09	1264.18	1264.39	1268.17	1270.82
Netherlands	1171.38	1171.39	1177.70	1196.89	1196.97
Norway	1240.19	1245.60	1250.13	1282.49	1287.75
New Zealand	1270.97	1275.70	1287.73	1308.45	1308.48
Sweden	1470.11	1472.52	1474.12	1670.07	1670.92
US	1608.01	1609.98	1610.00	1644.49	1645.20
S. Africa	1330.70	1331.02	1331.39	1413.80	1415.80

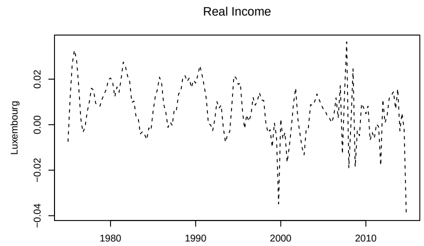
Note: Robustness results for identify model

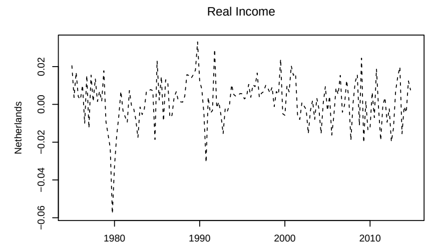
Figure 4.4.1: Income Growth

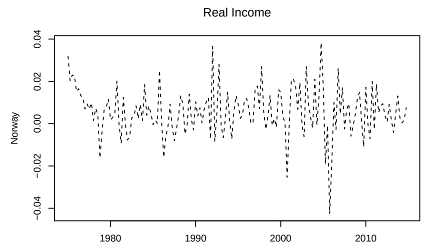


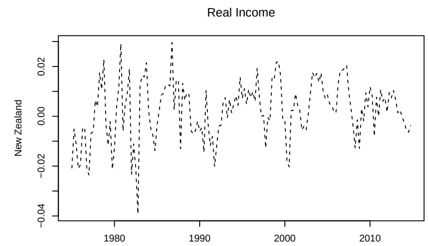

Real Income
Japan
1980
1990
2000
2010

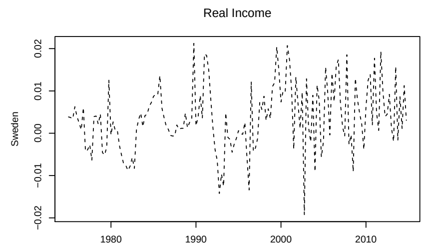

Real Income
S. Korea
1980
1990
2000
2010


Real Income
Luxembourg
1980
1990
2000
2010


Real Income
Netherlands
1980
1990
2000
2010


Real Income
Norway
1980
1990
2000
2010

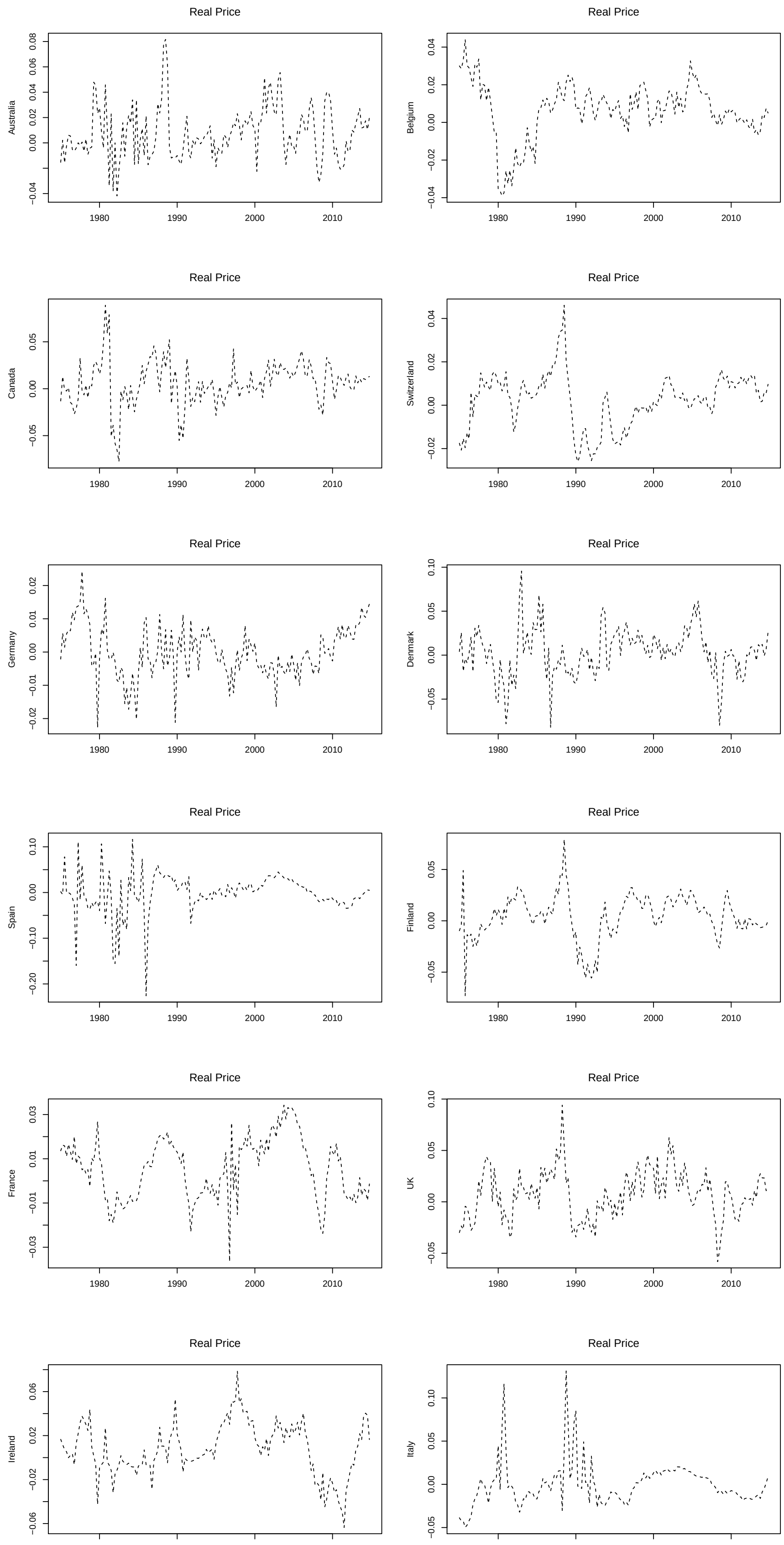

Real Income
New Zealand
1980
1990
2000
2010

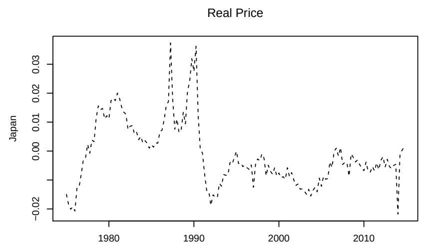

Real Income
Sweden
1980
1990
2000
2010

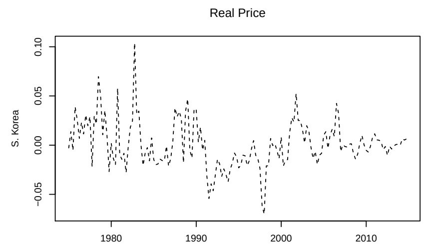

Real Income
US
1980
1990
2000
2010

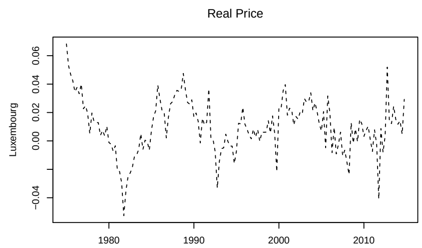

Real Income
S. Africa
1980
1990
2000
2010

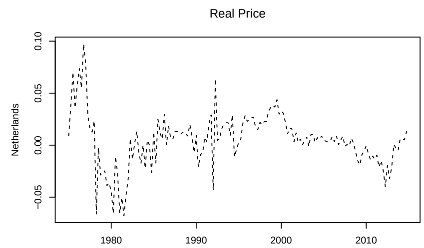
Figure 4.4.2: Housing Price Growth

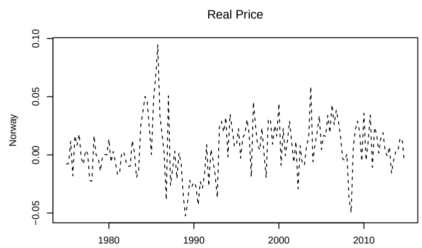


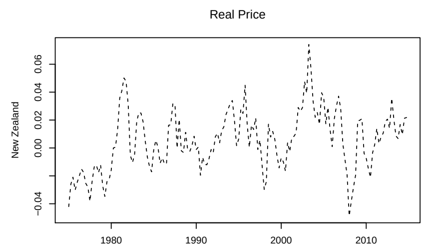

Real Price
Japan
−0.02
0.00
0.01
0.02
0.03
1980
1990
2000
2010

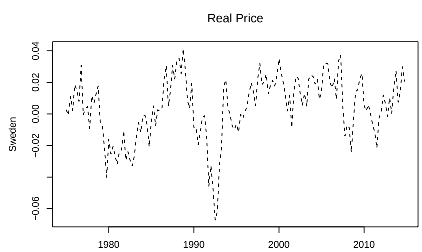

Real Price
S. Korea
−0.05
0.00
0.05
0.10
1980
1990
2000
2010

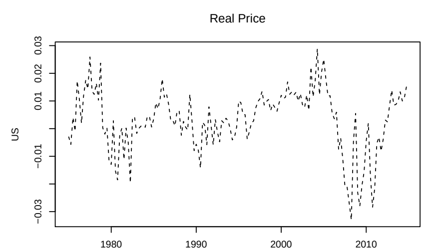

Real Price
Luxembourg
−0.04
0.00
0.02
0.04
0.06
1980
1990
2000
2010


Real Price
Netherlands
−0.05
0.00
0.05
0.10
1980
1990
2000
2010


Real Price
Norway
−0.05
0.00
0.05
0.10
1980
1990
2000
2010


Real Price
New Zealand
−0.04
0.00
0.02
0.04
0.06
1980
1990
2000
2010


Real Price
Sweden
−0.06
−0.02
0.00
0.02
0.04
1980
1990
2000
2010


Real Price
US
−0.03
−0.01
0.01
0.02
0.03
1980
1990
2000
2010

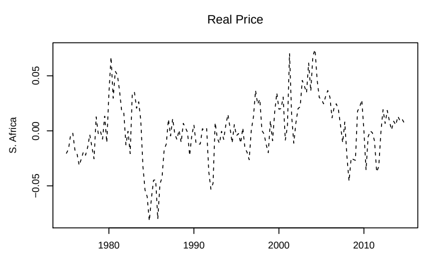
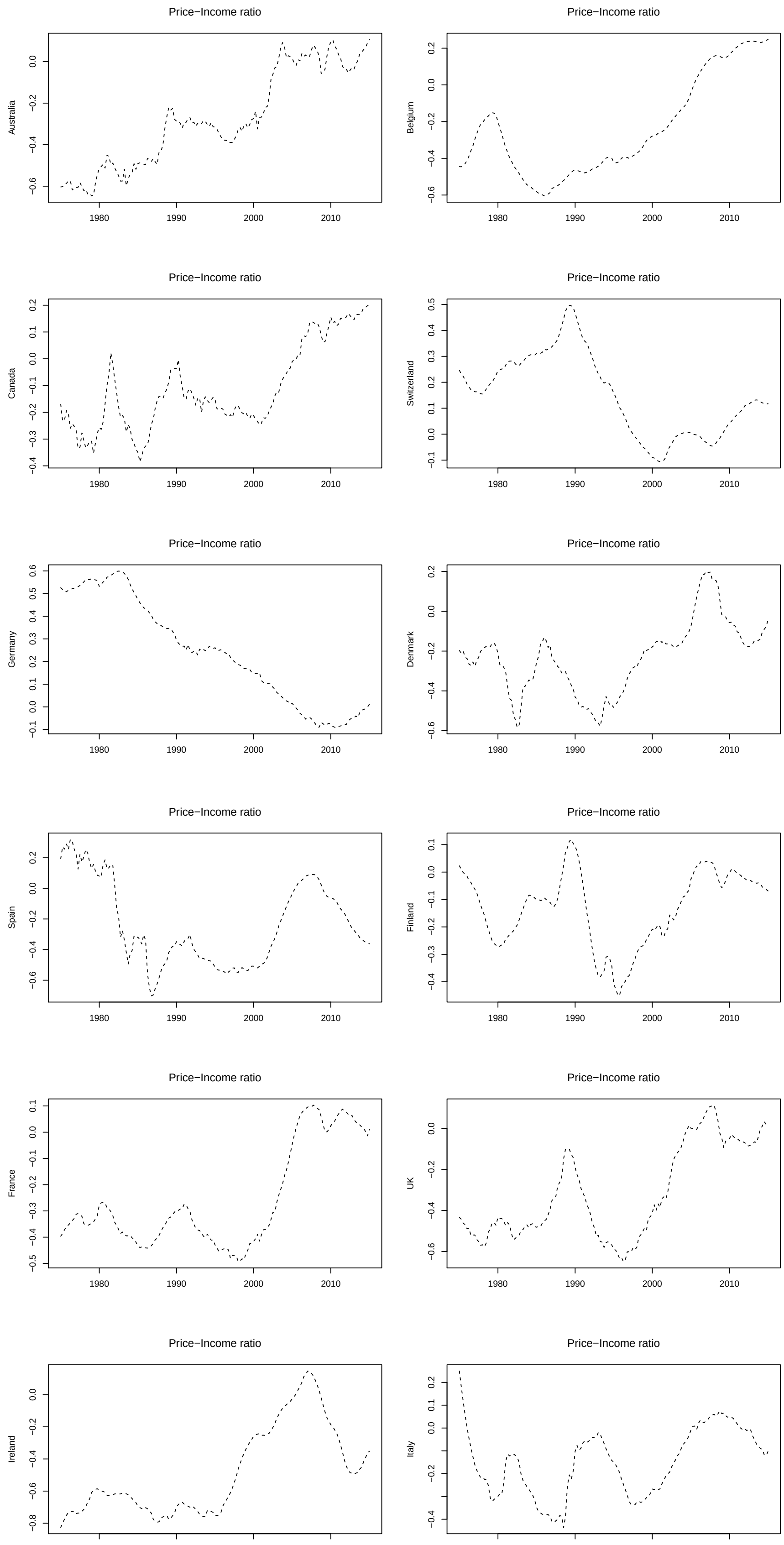

Real Price
S. Africa
−0.05
0.00
0.05
1980
1990
2000
2010

Figure 4.4.3: Price-Income Ratio



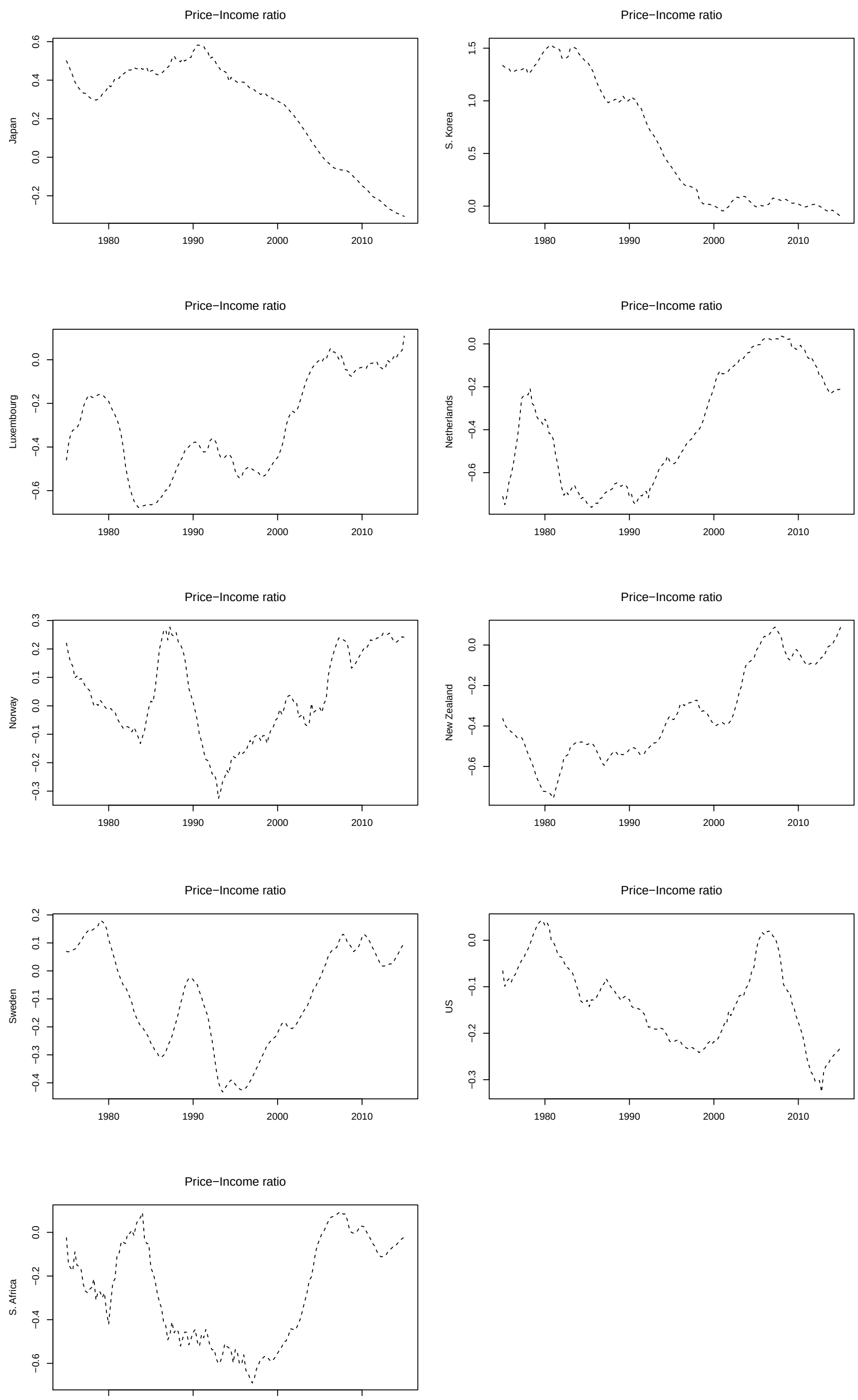
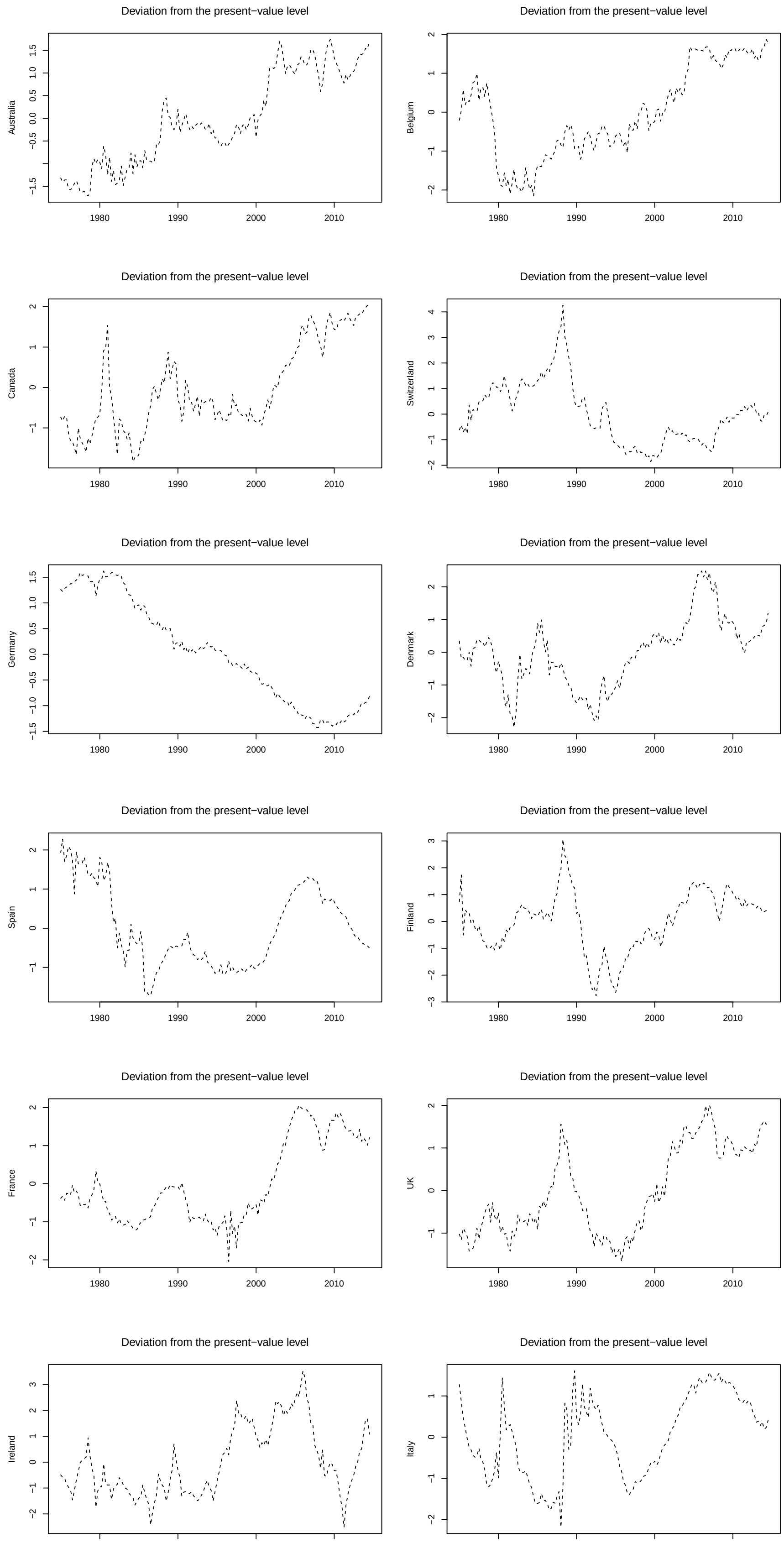
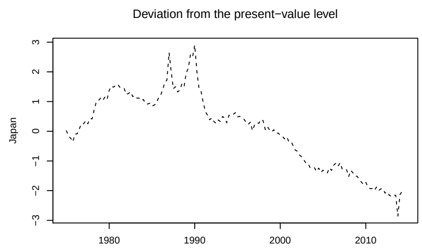
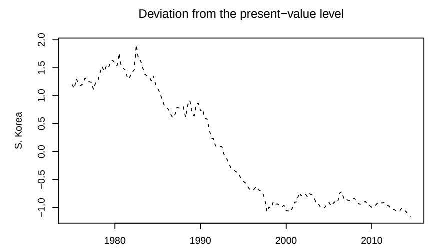
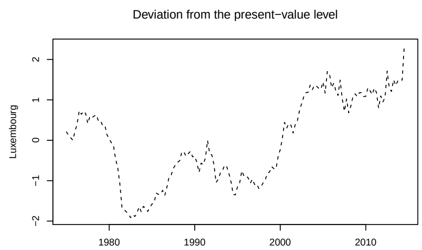

Price−Income ratio
Japan
Price−Income ratio
S. Korea
Price−Income ratio
Luxembourg
Price−Income ratio
Netherlands
Price−Income ratio
Norway
Price−Income ratio
New Zealand
Price−Income ratio
Sweden
Price−Income ratio
US
Price−Income ratio
S. Africa
1980
1990
2000
2010

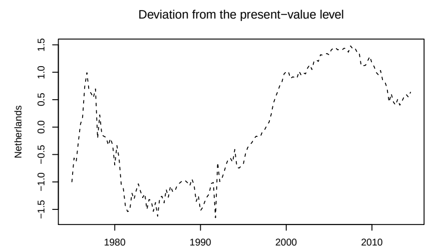
Figure 4.4.4: Deviation from the present-value level

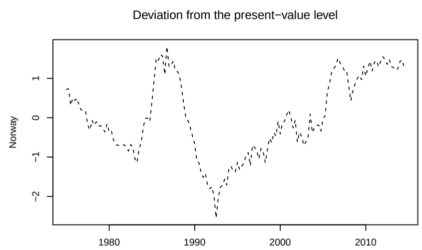


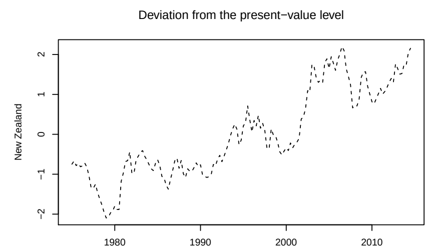

Deviation from the present−value level
Japan
3
2
1
0
−1
−2
−3
1980
1990
2000
2010

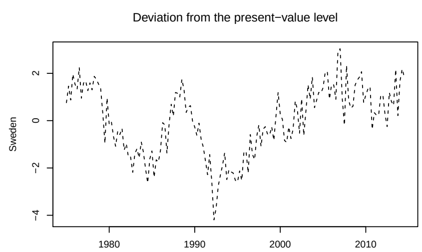

Deviation from the present−value level
S. Korea
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
1980
1990
2000
2010

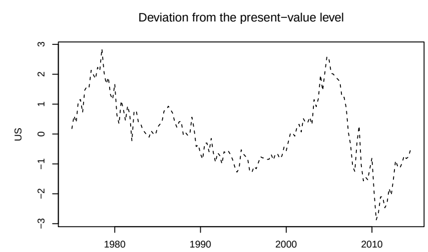

Deviation from the present−value level
Luxembourg
2
1
0
−1
−2
1980
1990
2000
2010

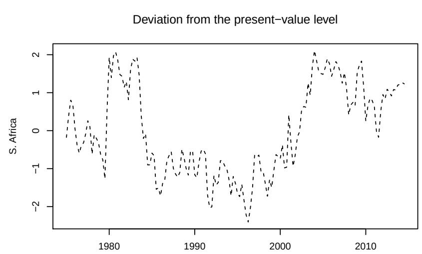

Deviation from the present−value level
Netherlands
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
1980
1990
2000
2010


Deviation from the present−value level
Norway
1
0
−1
−2
1980
1990
2000
2010


Deviation from the present−value level
New Zealand
2
1
0
−1
−2
1980
1990
2000
2010


Deviation from the present−value level
Sweden
2
0
−2
−4
1980
1990
2000
2010


Deviation from the present−value level
US
3
2
1
0
−1
−2
−3
1980
1990
2000
2010


Deviation from the present−value level
S. Africa
2
1
0
−1
−2
1980
1990
2000
2010

4.5 Appendix

4.5.1 Modified Present-Value Model

We decompose the price-income ratio into the present-value of expected income growth, the present-value of expected housing price growth, and a non-stationary component(Z).

$$p_t - y_t = \mu + \sum_{i=0}^{\infty} E_t(\triangle y_{t+j} - \triangle p_{t+i}) + Z_t \tag{4.10}$$

We assume that the expected house price and expected income growth are latent variabels and there is a non-stationary deviation from the long run stationary value of price-income ratio which contain the future expected housing price, the future expected income growth, and a non-stationary residuals term. We assume the expected price growth and expected income growth as AR(1) processes, while the Z component follows a random walk process.

$$\triangle y^e_{t+1} = \delta_1 + \beta_1 \triangle y^e_t + \varepsilon^{y^e}_{t+1}, \varepsilon^{y^e}_{t+1}\ iidN(0, \sigma^2_{y^e}) \tag{4.11}$$

$$\triangle p^e_{t+1} = \delta_2 + \beta_2 \triangle y^e_t + \varepsilon^{p^e}_{t+1}, \varepsilon^{p^e}_{t+1}\ iidN(0, \sigma^2_{p^e}) \tag{4.12}$$

$$z_{t+1} = \delta_3 + z_t + \varepsilon^{z}_{t+1}, \varepsilon^{z}_{t+1}\ iidN(0, \sigma^2_{z}) \tag{4.13}$$

where

$$\triangle y^e_t = E_t[\triangle y_{t-1}]$$

$$\triangle p^e_t = E_t[\triangle p_{t-1}]$$

To get modified present-value model, we define the relationship between the realized real income growth and realized housing price growth such as:

$$\triangle y_{t+1} = \triangle y^e_t + \varepsilon^{y}_{t+1} \tag{4.14}$$

$$\triangle p_{t+1} = \triangle p^e_t + \varepsilon^{p}_{t+1} \tag{4.15}$$

Based on our definition, ε^{y}_{t+1} and ε^{p}_{t+1} are an idiosyncratic shock. Plugging Eqs. 3-7 in 2 and solving, we get:

$$p_t - y_t = A + B_1 \triangle y^e_t + B_2 \triangle p^e_t + z_t \tag{4.16}$$

where $A = \mu + (\gamma_1 * \delta_1) + (\delta_2 * \gamma_2)$, $B_1 = \delta_1 * \beta_1$ and $B_2 = \delta_2 * \beta_2$. Equation 9 is the modified present-value model for housing market, which determined the log price-income ratio is linear in the expected real income growth y^e_t , expected real housing price growth p^e_t, and the residual term prv_t. There are five shocks in the model, a shock to expected real income growth ($\varepsilon^{y^e}_{t+1}$), a shock to expected real housing price growth ($\varepsilon^{p^e}_{t+1}$), a shock to the PVR component ($\varepsilon^{pvr^e}_{t+1}$), a shock to realized income growth (ε^{y}_{t+1}), and a shock to the realized housing price (ε^{p}_{t+1}). We use a state space approach for the present-value model, where the measurement equation can be written as:

$$\begin{bmatrix} p_t - y_t \\ \delta y_{t+1} \\ \delta p_{t+1} \end{bmatrix} = \begin{bmatrix} A \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & B_1 & B_2 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Z_t \\ \delta y_t \\ \delta p_t \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon^{y}_t \\ \varepsilon^{p}_t \end{bmatrix}$$

and the transition equation is represented as:

$$\begin{bmatrix} \delta y^e_t \\ \delta p^e_t \\ Z_t \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ 0 \end{bmatrix} + \begin{bmatrix} \beta_1 & 0 & 0 \\ 0 & \beta_2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \delta y^e_{t_1} \\ \delta p^e_{t_1} \\ Z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon^{y^e}_t \\ \varepsilon^{p^e}_t \\ \varepsilon^{z}_t \end{bmatrix}$$

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